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**A PRESCRIPTIVE KNOWLEDGE VISUALIZATION MODEL
FOR STUDENT PERFORMANCE BASED ON INTERNET
USE BEHAVIOR (IUB)**



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**DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
2023**



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Abstrak

Visualisasi dan data tafsiran mengenai penggunaan Internet adalah salah satu elemen penting untuk menentukan tingkah laku penggunaan Internet pelajar (IUB). Istilah IUB merujuk kepada aktiviti dalam talian oleh pelajar. Walau bagaimanapun, proses ini mempunyai kelemahan yang ketara dari segi kognitif dan penaakulan dalam analisis preskriptif untuk menentukan kesan IUB terhadap prestasi pelajar. Oleh itu, kajian ini bertujuan untuk mencadangkan model Visualisasi Pengetahuan Preskriptif (PKV) dengan menggunakan komponen kognitif dan penaakulan. Kajian ini menggunakan reka bentuk metodologi penyelidikan sains, yang terdiri daripada empat fasa; takrifan tentang masalah, cadangan, pembangunan dan penilaian. Pada mulanya, analisis kandungan telah dijalankan untuk mengenalpasti elemen Visualisasi Pengetahuan dalam konteks pendidikan. Model yang dicadangkan telah dibina berdasarkan hasil analisis kandungan tiga komponen utama; Visualisasi Pengetahuan, analitik preskriptif dan tingkah laku penggunaan Internet (IUB). Teori asas model PKV bersandarkan kepada teori Visualisasi Pengetahuan Preskriptif, teori Beban Kognitif dan teori Pembuatan Keputusan. Model itu kemudiannya disahkan dan diterima oleh pakar domain. Selepas itu, tujuh dimensi pengesahan model PKV dikemukakan; kerumitan, keterlihatan, fleksibiliti, kejelasan, kebolehdan, kepraktisan dan keberkesanan. Pengesahan model dijalankan dalam tiga fasa; melalui semakan pakar, penilaian heuristik dan penilaian asas pengetahuan. Dapatan kajian menunjukkan bahawa keputusan penilaian model PKV mendapat skor min tertinggi 9.67 (daripada 10) dari semua dimensi dan menunjukkan model PKV yang dicadangkan menghasilkan asas pengetahuan yang boleh dimasukkan ke dalam sistem dan relevan dalam sektor pendidikan dalam menyokong proses membuat keputusan berkaitan peningkatan prestasi pelajar. Secara teorinya, kajian ini menyumbang kepada peningkatan visualisasi dan tafsiran data dengan menggunakan komponen kognitif dan penaakulan dalam analitik preskriptif. Selain itu, model yang dicadangkan membolehkan pembuat keputusan dalam domain pendidikan membuat keputusan yang bermakna mengenai penggunaan Internet.

Kata kunci: Analitik preskriptif, Visualisasi Pengetahuan, Tingkah laku penggunaan Internet, Prestasi pelajar, Institusi Pengajian Tinggi.

Abstract

The visualization and interpretation of the Internet usage data is one of the key elements to determine students' Internet use behavior (IUB). The term IUB refers to online activities by the students. However, these processes have significant shortcomings in terms of cognitive and reasoning in prescriptive analytics for determining the impact of IUB on student performance. Therefore, this study aims to propose a Prescriptive Knowledge Visualization (PKV) model by using cognitive and reasoning components. This study employed a design science research methodology comprising four phases; problem definition, suggestion, development and evaluation. Initially, a content analysis was conducted to investigate the components of Knowledge Visualization in an educational context. The proposed model was constructed based on the content analysis results of three main components; Knowledge Visualization, prescriptive analytics and Internet use behavior (IUB). The underlying theory of PKV model was based on Prescriptive Knowledge Visualization Theory, Cognitive Load Theory and Decision-Making Theory. The model was then verified and accepted by domain experts. Subsequently, seven PKV model validation dimensions were put forward; complexity, visibility, flexibility, clarity, manageability, practicality and effectiveness. The model validation was conducted in three phases; expert review, usability testing and knowledge base evaluation. The findings indicate that the PKV model's evaluation results score the highest mean of 9.67 (out of 10) of all dimensions and indicate that the proposed PKV model is producing a knowledge base that can be inserted into the system and relevant in the education sector, particularly in supporting the decision process related to the improvement of student performance. Theoretically, this study contributes in enhancing the visualization and interpretation of data by using cognitive and reasoning components in prescriptive analytics. Besides, the proposed model enables decision makers in the educational domain to make meaningful decisions regarding Internet usage management.

Keywords: Prescriptive analytics, Knowledge Visualization, Internet use behavior, Student performance, Higher Learning Institution.

Acknowledgement

All praises and thanks to the Almighty Allah (SWT) who gave me the opportunity, strength, and the ability to complete my study. No volume of words to express my sincere gratitude towards my supervisor Assoc. Prof. Dr. Azizah Binti Hj Ahmad and Assoc. Prof. Dr. Mazida Binti Ahmad, for the continuous support of my Ph.D. study and related research, for their patience, motivation, and immense knowledge. Their guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better supervisor and mentor for my Ph.D. study. Without their guidance and knowledge this study would not have been complete.

My special gratitude is also dedicated to my parents; my late father Khamis Bin Awang and Rahmah Binti Ahmad, a special thanks to my partner @ husband; Mohd. Syahrul Azilan Bin Mat Isa, my children; Rayyan, Syakira, Rifian and Rifaul, and to all my family members for their endless supports, sacrifice and prayers. Words cannot express how grateful I am to my family for all the sacrifices they have made on my behalf. Their prayer for me was what sustained me thus far.

My sincere thanks also go to my fellow doctoral students for their feedback, cooperation, and friendship. All my friends provided me an opportunity to share my research struggle and stimulate discussions. Without their precious support, it would not be possible to conduct this research.

My special thanks are extended to the Institute for Advanced and Smart Digital Opportunities, the Dean of School of Computing (SOC), all lecturers and SOC staff for providing the enabling environment for PhD students. Finally, I also indebted to the Ministry of Education, Malaysia that has funded my study under MyBrain, and to the individuals that have directly and indirectly assisted me in every phase of this research. May Almighty ALLAH bless and reward you for all the good deeds.

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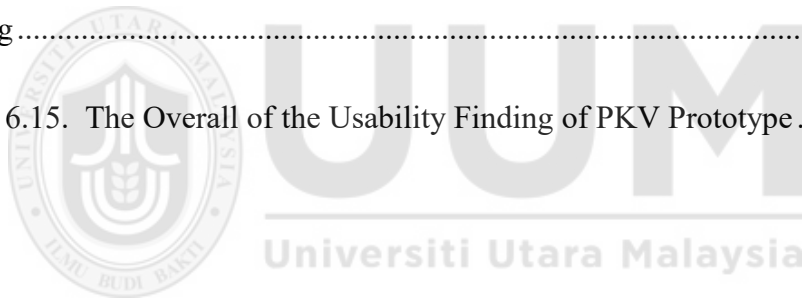
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List of Abbreviations

CLT	Cognitive Load Theory
CVI	Content Validity Index
CVM	Conceptualization Visual Models
DIKW	Data-Information-Knowledge-Wisdom
DM	Data Mining
DSS	Decision Support System
DV	Data Visualization
EVM	Externalization Visual Models
IHL	Institution of Higher Learning
INFOVIS	Information Visualization
IT	Information Technology
IUB	Internet Use Behavior
IVM	Internalization Visual Model
KDD	Knowledge Data Discovery
KV	Knowledge Visualization
PVT	Process Visualization Theory
PKV	Prescriptive Knowledge Visualization
SPSS	IBM SPSS Statistics
UUM	Universiti Utara Malaysia
WV	Wisdom Visualization

CHAPTER ONE

INTRODUCTION

1.1 Background

The past few decades have seen an explosion in the integration of visualization in many fields like education, medical, engineering, science and technology, entertainment, business industries, and many more (Xu et al., 2019; Jamil et al., 2019; Lopez-Herrejon, Illescas, & Egyed, 2018; Liao et al., 2018 ; Said, Shamsudin, Mailok, Johan, & Hanaif, 2015). Today, visualization is used as an alternative medium to efficiently transfer information and knowledge acquisition in the fastest way using graphical representation or visual formats, such as charts and graphs (Javvaji, Harteveld, & El-Nasr, 2020). Nevertheless, among the challenges faced include the availability of abundance of data as well as determination of the appropriate technique for accessing, discussing, evaluating, and making sense out of the data (Burch & Schmauder, 2018). Despite the challenges, active use of visualization techniques can provide a powerful way to spot major structures and patterns rapidly (Protopsaltis, Sarigiannidis, Margounakis, & Lytos, 2020)

Visualization is based on the four layers of Data-Information-Knowledge-Wisdom (DIKW) hierarchy as introduced by Ackoff (1989). Each of the DIKW layers adds certain attributes over and above the previous one. For example, the most basic level, Data Visualization (DV), contains raw data, which has no meaning, whilst Information Visualization (InfoVis) provides context to data. Knowledge Visualization (KV) imparts ways of using information, whereas Wisdom Visualization (WV) offers insights on the time and purpose of using knowledge (Card, 1999). For the past ten years, various KV methods have been invented and

widely utilized for representing, conveying, and accessing knowledge using all kinds of visual elements, following InfoVis and DV (Scharl et al., 2016; Burkhard, & Meier, 2005).

To enable effective process visual representations, InfoVis and KV are exploiting one's innate even though the usage differs in both domains. InfoVis aims to explore large amounts of abstract data to derive new insights or simply make the stored data more accessible. In contrast, KV improves the creation and transfer of knowledge by providing richer means of expressing one's understanding. While InfoVis typically helps to improve information access and retrieval, including the presentation of large data sets, particularly in the aspect of human and computers interaction, KV primarily aims at augmenting knowledge-intensive communication between individuals by relating new insights to deliver meaningful data into action (Wang, & Tao, 2017). In addition, the goal of KV is to increase the generation and delivery speed of knowledge between people by giving people rich ways to express what they know (Liu et al., 2021; Constant, 2020; Schots et al., 2015). Although they have succeeded in creating new insights based on abstract data (Bae, Falkman, Helldin, & Riveiro, 2019), the InfoVis researchers do not really concentrate on the transferring mechanism (Ware, 2019; Franconeri, Padilla, Shah, Zacks, & Hullman, 2021). This problem should be addressed by introducing KV to assist users in comprehending situation better.

KV can be a powerful cognitive tool in dealing with problem solving and decision-making process and can be seen as human centered approach to knowledge discovery (Biagi, Patriarca & Di Gravio, 2022; Killen, Geraldi, & Kock, 2020; Sacha et. al, 2014). In relation to that, KV has been used in education for more than ten years to facilitate decision maker in cognitive processing and retaining knowledge (Linden,

Liu, & Colot, 2017; Santos, Ferreira, & Dias, 2016). More specifically, KV is used by the Institutions of Higher Learning (IHL) management to visualize performance analysis and create the understanding of data, as well as to produce quality decision (Vieira, Parsons, & Byrd, 2018; Zhu, Yu, & Riezebos, 2016). Since academic performance analysis is becoming increasingly critical, IHL must assure a standard quality of service to provide better learning environment for students (Ahmad, R., Ahmad, R., Sagir, & Jaafar, 2020; Dei, 2019; Coffrin, Corrin, De Barba & Kennedy, 2014).

Internet usage among students has been the most targeted research area in academic performance analysis for the past decades (Demir, & Kutlu, 2018; Siddiqi & Memon, 2016). The wide access to the Internet related technologies has improved people's lives and provides great opportunities, especially for students. Hence, most governments all over the world are determined to invest heavily on the technologies (Omar et. al, 2018; Posso, 2016; Waithaka, 2013). Due to several factors, such as the teaching and learning environment that has shifted to online, especially during the critical phase, governments have given all out to provide students with the Internet infrastructure. Eventually, this has been broadly accepted and used as an assessment measure towards quality education (Muhonen, Pakarinen, Lerkkanen, Barza, & von Suchodoletz, 2020; Martínez-Caro, Cegarra-Navarro, & Alfonso-Ruiz, 2020). However, along with the tremendous growth of the Internet and its use, there is a growing concern that this investment does not lead to the desired goal of increasing productivity and quality (Xu, Wang, Peng, & Wu, 2019; Khamis, Ahmad, & Muraina, 2018). The main reasons for the above concern is that these resources are predominantly used for non-academic activities especially social networking and entertainment, which that will give huge impact on the students' performance

(Marker, Gnambs, & Appel, 2018; Celestine, & Nonyelum, 2018; Ravizza, Uitvlugt, & Fenn, 2017).

Recognizing the main Internet usage factors of students' academic performance and taking preventive and interventional strategies can help in increasing students' performance and thus improve the quality of educational level (Menon, Narayanan, & Kahwaji, 2018; Omar, Ahmad, Azman Yasin, Ghazali, & Khamis, 2018b). One of the greatest challenges faced today is to make sense out of all this data (Ghasemaghaei, Ebrahimi, & Hassanein, 2018; Zhu, Yu, Wang, Ning, & Tang, 2018; Coveney, Dougherty, & Highfield, 2016; Dumbill, 2013). In this regard, the use of data analytic tools can be a step toward identifying and extracting factors that affect students' educational failure. Data analytic has long been applied in education, especially the higher educational domain because one of the important roles played by the management is to come up with a correct planning that will lead to the successful implementation of educational programs and academic quality (Ang, Ge, & Seng, 2020; Fernandes et. al, 2019; Aldowah, Al-Samarraie, & Fauzy, 2019; Adekitan, & Noma-Osaghae, 2019; Rodrigues, Isotani, & Zárate, 2018). Without proper planning and evaluation, issues regarding the students' failure will give negative impacts on the IHL (Sarraf, Fontanella, & Di Zio, 2019; Ray & Saeed, 2018).

The use of data analytics in IHL becomes a prominent approach to predict students' failure rate and allow the IHL to make strategic decisions on the early stage on how to foster that issue in the most effective way (Saa, Al-Emran, & Shaalan, 2019; Hussain et al., 2019; Asif et. al, 2017; Saa, 2016). In addition, a decision maker may adopt a specific method to help those students who are at-risk to get back on track to perform their full potential. The descriptive and predictive analytics that have been popular in recent years in higher education are at the midpoint of the data analytics

evolution (Gil, Martins, Moro, & Costa, 2020; Dutt, Ismail, & Herawan, 2017; Devasia, Vinushree, & Hegde, 2016). The two known analytics led to a new evolution in the analytical world, which is prescriptive analytics. The prescriptive analytics took prediction to the next level by recommending actions that influence future anticipation (Lepenioti, Bousdekis, Apostolou, & Mentzas, 2021; Bertsimas & Kallus, 2020; Tonidandel, King & Cortina, 2018; Srinivas & Ravindran, 2018). This type of analytics has been gaining considerable attention from other researchers as well because it has the potential to assist institutional decision-makers in producing smarter and faster decisions (Frazzetto, Nielsen, Pedersen, & Šikšnys, 2019; Van Poucke, 2016; Soltanpoor & Sellis, 2016).

Prescriptive analytics is also new to the business planning and advanced analytics domains (Frazzetto, Nielsen, Pedersen, & Šikšnys, 2019; Evans, 2017; Krumeich, Werth, & Loos, 2016). For the first domain, the analytics helps to translate a forecast into a feasible plan for the business and to identify the best steps to implement (Drake, & Walz, 2018; Schmarzo, 2015). The analytics method is widely used in healthcare to recommend alternative treatments to clinicians and patients and help in the decision-making process (Spruit & Lytras, 2018; Dinov, 2016; Mathew & Pillai, 2015). Most importantly, prescriptive analytics allows data scientists to obtain insight on necessary actions in reducing risks and improving the quality of decisions (Raja, Mukherjee, & Sarkar, 2020; Wanigarathna, Sherratt, Price, & Austin, 2016).

The same analytics concept was applied this study, specifically in the education domain to determine the impact of Internet on students' academic performance. This study focuses on various Internet activities performed by students that affect their academic results. Furthermore, the newly developed data analytics offers unique opportunities, such as generating suggestions along with possible alternative

solutions to be implemented in providing greater impact on students' performance. The main interest explored in this study refers to the integration of visualization with prescriptive analytics to analyze students' performances.

1.2 Problem Statement

The Institutions of Higher Learning (IHLs) have always emphasized on the value of quality education since it is recognized as the key aspect to improve students' achievement (Deniz & Geyik, 2015). Therefore, to guarantee the highest level of quality education, the IHLs should provide good Internet infrastructure (Maslac & Magzan, 2012). This is important because Internet technology is a powerful educational tool to facilitate the learning process (Ramlan & Ahmed, 2010). At the same time, students' life without Internet access is hard to imagine nowadays. Unfortunately, Internet also offers unpleasant possibilities, which may be harmful to the students' academic experiences (Harper & Hodgins, 2016; McBride & Derevensky, 2012). One example of how internet usage can impact student performance is through its influence on distractions and time management. While the internet provides a wealth of educational resources, it also offers numerous distractions in the form of social media, entertainment websites, online gaming, and other non-academic content. Excessive or unregulated internet usage can lead to reduced focus, procrastination, and poor time management, ultimately affecting students' academic performance. The issue on poor academic performance among students due to Internet usage has been intensely debated by academicians recently (Xu, Wang, Peng, & Wu, 2019; Shahibi & Rusli, 2017; Siraj et. al, 2015). However, past studies reveal inconsistent and contradicting results (Englander, Terregrossa, & Wang, 2010). Therefore, further study is required to assess the impact of Internet usage on students' academic performance in achieving quality education in IHLs.

One way to determine the impact of Internet usage is by discovering knowledge from educational data to study the main attributes that may affect the students' performance (Mishra, Karthikeyan, Barman, & Veetil, 2020; Rahman, Deep, & Rahman, 2016). However, the handling the massive amount of educational data is challenging due to multidimensional type of data such as video, audio, file transfer, games and many more medium (Adnan, & Akbar, 2019; Dorji, 2015). Hence, analytics technologies are needed to extract valuable knowledge from the huge volume of data accumulated at a very fast speed through continuous streaming (Wiener, Saunders, & Marabelli, 2020; Mikalef, Pappas, Krogstie, & Pavlou, 2019; Peltzer, Pengpid, & Apidechkul, 2014). Most of the previous related studies only focused on outlining and predicting the impact of Internet usage pattern on student performance without prescribing the best action to improve their achievement (Xu et al., 2019). Having only the prediction results is not enough for a decision-maker to decide on certain action without knowing the consequences. For example, predictive analytics can only indicate what will happen to a student based on Internet usage patterns but gives no guidance on the decisions that need to be made. Therefore, it should provide a decision-maker with an automatic data-backed decision options that is able to weigh out the best choice in reducing decision risks (Sahoo, Gulati & Haq, 2021; Halde, 2016; Mat, Buniyamin, Arsad, & Kassim, 2013). The discovered options can be used to offer helpful and constructive recommendations to the academic planners to enhance their decision-making process, improve students' academic performance, reduce the failure rate, and understand students' behavior (Cerretani, Iturioz, & Garay, 2016; Ayub, Hamid, & Nawawi, 2014; Ogedebe, 2012; Wanajak, 2011).

The limitation of predictive analytics in turning descriptive results into concrete decisions calls for prescriptive analytics as an optimal next step to drive recommendations. Generating automated decisions or recommendations requires specific and unique algorithmic models, including clear direction from those utilizing the analytical technique (Veale, Van Kleek, & Binns, 2018; Donkers, Loepp, & Ziegler, 2017). For the past five years, there are growing numbers of research on adapting this new advance analytics approach to ensure organizations can remain competitive and relevant in the current business environment (Gepp, Linnenluecke, O'Neill, & Smith, 2018). Currently, prescriptive analytics has been successfully implemented in business organizations, while the usage in higher educational institutions is still relatively new. Moreover, studies show that the use of prescriptive analytics in the field of education needs further research (Deshpande, Sharma, & Peddoju, 2019).

One of the biggest challenges faced by IHLs today is to improve the quality of managerial decisions (De Wit, & Altbach, 2021; Rashid, & Yadav, 2020; Tari & Dick, 2016). The managerial decision-making process becomes more complex as educational data are captured from different sources and generated on a daily basis in various formats (Stander & Herman, 2017). The data generated will be wasted if not used for good purposes in improving the education level (Brown, Barry, & Ku, 2020). In addition, educational data that is often complex and disorganized that makes it almost impossible to conventionally processed (Xavier & Meneses, 2021). Hence, a visual-based data analysis that can make sense out of the huge data is necessary (Ang, Seng, Zungeru, & Ijamaru, 2017).

In the field of Business intelligence or data analytics, the insights in visual form are tremendously helpful. It will be easier to comprehend the consumption of insights

and take decisive action by using such analytics (Wamba et al., 2017; Barton, & Court, 2012). However, previous studies mostly focused on information visualization, which only delivered meaningful data without any action (Chen, 2017). Since Big Data has already provided users with the opportunity to conduct prescriptive analytics, the techniques that computationally determine available actions, including their consequences and alternatives, can be applied given the engagement's complexities, rules, and constraints (Sappelli, de Boer, Smit, & Bomhof, 2017)

Design Science Research provides prescriptive knowledge with a basis for translating theory into practice (Avdiji, & Winter, 2019; Gregor & Hevner, 2013; Hevner, March, Park, & Ram, 2004). Recently, prescriptive knowledge is utilized in the healthcare sector to assist medical practitioners in prescribing drugs (Khemmarat & Gao, 2016; Warren, Gu, Kennelly, & Boyce, 2014; MacKinlay & Verspoor, 2012) and also to support a patient's condition and their recovery at home (Simmons, McCrindle, Sperrin, & Smith, 2013). Several researchers have highlighted that it would be valuable to expand the scope of the prescriptive or design knowledge (Abbasi, Adjero, Abate & Zheng, 2019; Goes, 2014) and to repeat this exercise to identify and draw links by establishing theoretical contributions in other different associated areas, especially IS (Sivarajah, Kamal, Irani, & Weerakkody, 2017). Unfortunately, there is a lack of research on prescriptive knowledge in the context of IS, as stated by Seidel and Watson (2014).

Based on the preceding discussion, this study proposes to apply the Visual Analytic Model to derive more value from datasets that continue to increase in complexity and size, which is Big Data. The Visual Analytics approach has been used in several research projects, helping users to understand data as well as generate knowledge from the analyzed dataset (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015).

Many theoretical works have also examined the role of the Visual Analytic tools in data analysis, decision-making, and problem solving (Tam, Kothari, & Chen, 2016; Sacha et al., 2014; Crouser, Hescott, & Chang, 2014; Chen & Janicke, 2010). It is also known as a promising approach for the integration of domain knowledge to the analysis process (Batista, Correa, & Palanisamy, 2016). However, existing studies only concentrated on how visualization works and interacts between data, computer, and humans, without considering the elements of human cognitive and reasoning (Sacha et al., 2014). The combination of these three elements cannot determine which of the infinitely many valid conclusions are sensible to draw. Strangely, the theories that adopt logic as their account of deductive competence have almost universally overlooked this problem (Gomes, Araujo, & Jelihovschi, 2022). Thus, to represent a complete approach, Visual Analytics requires not only computational analytics but also the ability to mentally process the data (Moran, Gadepally, Hubbell, & Kepner, 2015; Mnguni, 2018; Mnguni, 2014) and understanding, which refer to the cognitive and reasoning analytics (Green & Maciejewski, 2013) through the use of visualization. The cognitive and reasoning element is significant lesson from the study of decision making is the need for experiments to examine realistic problems (Perkhofer, Hofer, Walchshofer, Plank, & Jetter, 2019). To achieve the prescriptive analytics goals, the cognition and reasoning elements should be added in a new model of this study. Therefore, the researcher intends to fill this research gap in this study.

1.3 Research Questions

This study aims of answering the following questions:

- 1) What are the main components of Prescriptive Knowledge Visualization (PKV) model?
- 2) How to develop the Prescriptive Knowledge Visualization (PKV) model by using cognitive and reasoning elements?
- 3) How to evaluate the Prescriptive Knowledge Visualization (PKV) model?

1.4 Research Objectives

To answer the research questions posed above, the following research objectives are formulated:

- 1) To investigate the main components of Prescriptive Knowledge Visualization (PKV) model.
- 2) To develop the PKV model by using cognitive and reasoning elements.
- 3) To evaluate the PKV model by using expert review.

1.5 Scope of the Study

This study focuses mainly on development of PKV model using cognitive and reasoning elements. Therefore, to address the scope of this study, the components of the model address the Knowledge Visualization for the representation and presentation of data. This study highlights on the level of expertise of the IHL's policy makers before developing the system for visual purposes to support the decisions. The main target participants are the members of the management team, either at the school, faculty, or senate level, who are responsible in making various organizational decisions.

Since the domain area of this study is to develop and evaluate a conceptual model that addresses the relationship between Internet usage and students' academic performance in Institutions of Higher Learning (IHLs), this study focuses on the

undergraduate students of Universiti Utara Malaysia (UUM) of the years between 2017 to 2019. Students' Internet usage refers to students' access log, consisting of UUM Wifi networks, namely UUMWiFi and UUMWiFi_Guest. Students' access log, which records all students' Internet activities, has filtered the following fields; IP Address, Web Site URL, Date and Time, in and out bandwidth, and number of attempted connections. Students' Cumulative Grade Point Average (CGPA) represents the data for measuring students' academic performance for each semester.

In addition, this study concerns on evaluating the applicability of the proposed model to cater the domain issue in IHL. Hence, this study use expert review, usability testing from the prototype and expert review to evaluate the knowledge based on the prototype results as a technique to evaluate PKV model. This knowledge based is conducted by using expert review from decision maker in IHL to validate and certified the proposed PKV model.

1.6 Significance of Study

The significant study covers two aspects, theoretical and practical, as explained in the following sub-sections.

1.6.1 Theoretical

Most of the related studies on the descriptive and predictive analytics only looked into students' performance based on their Internet usage patterns. This indicates a gap that requires further research (Oskouei, Askari, & Sajja, 2013). Therefore, the current study adds new information by incorporating the visualization approach and prescriptive analytics into single conceptual model. Furthermore, the theories, concepts, and methodologies reviewed and utilized in this study (as described in Chapter 2 and 3) are relevant to captures IHLs' students' Internet usage data to

support decision-makers in improving students' academic performance, which also signifies as one of the most prominent theoretical contributions.

1.6.2 Practical

The findings of this study contribute to the benefit of Higher Institutions in assessing the extent of the impact on student achievement with all the facilities provided by the universities. Based on the results, the organizations may take necessary action to improve or control the purpose of learning. Many advantages can be explained to identify the patterns of student Internet usage and institutional educators, such as:

1. For Administrators and system managers; to improve and upgrade their strategies and improve the quality of their services based on the student's Internet usage pattern.
2. For the academic and teacher affairs; to identify the impact of Internet usage on student's academic performance and if necessary, the decision to restrict or make some restrictions for the use of any website during exam or special period in the semester.
3. If there is a meaningful relationship between the student and lecturer in the pattern of the use of any website, we may decide to provide the facility by the administrator to the peer connections rather than their usage behavioral equations.

This study provides valuable knowledge about the expert system with respect to its characteristics, working mechanism, components, and advantages. Fundamentally, this can assist expert system designers to apply this expertise and some mechanism from this model to develop systems in several domains. The techniques and methods comprise of some representation of expertise or a problem to be solved in the form of rules. Expert systems have been employed to assist and manage various problems in

the establishments by improving analyses and providing advice. Consequently, expert systems have been used to manage complicated problems that require considerable knowledge, thus enabling researchers and establishments to develop systems in several domains.

Furthermore, this research will benefit individuals and organizations by making the process of selecting the optimal way to visualize information to certain parties more efficient. It will also act as a future reference for researchers working in the fields of Knowledge Visualization and Prescriptive Analytics. Most significantly, this study will educate other researchers in the new field how to incorporate new data analytic approaches into their domain.

1.7 Research Frameworks

To ensure the study is systematically conducted, the following research and theoretical framework is followed through. Figure 1.1 illustrates the research and framework for this study as will be discussed in Chapter 3.

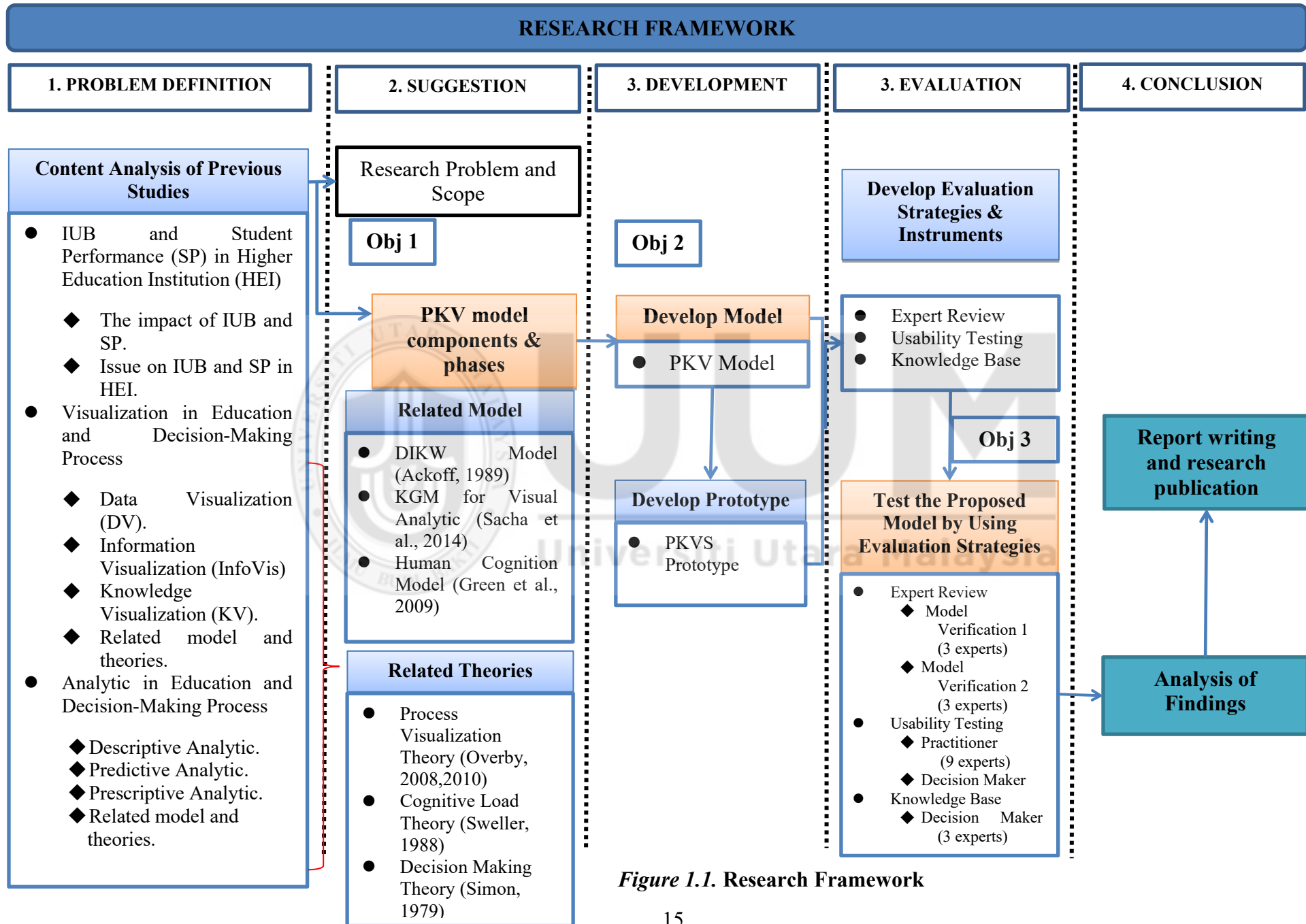


Figure 1.1. Research Framework

The research framework covered in this study followed the five phases which include problem definition, suggestion, development, evaluation, and conclusion. In the first phase (problem definition), a literature study and content analysis regarding concepts and theories were performed in identifying research problem and scope. Additionally, related theories and model were identified in the areas of IUB and student performances, KV and analytic in education.

In the suggestion phase, the reviewed theories and concepts were used as the basis in determining the components PKV model. The outcomes from this phase are model components which were related with the domain of this study which are to solve the issue of student performance based on IUB in higher education. In the development phase, the proposed PKV model was developed by combining all the related components as previously suggested. The prototype based on the PKV model was developed, and the usability test on PKVS prototype was conducted. The model was then evaluated in a combination of three stages (i.e., expert review, usability testing, and knowledge base). Finally in the conclusion phase, results from the evaluation phase were analyzed, concluded, and reported in publications.

1.8 Operational Definitions of Terms

For the purpose of clarification, the following terminologies are operationally defined:

a) Prescriptive Analytic

Prescriptive analytics is a form of data analytics that uses past performance and trends to determine what needs to be done to achieve future goals. In this study, prescriptive analytics is a process that analyzes data and provides instant

recommendations on how to optimize predicted student performance outcomes based on IUB.

b) Knowledge Visualization

Knowledge Visualization is the utilization of a visual or visuals to disseminate information to a person or persons. This visual information can take the form of a pie chart, bar chart, graph, presentation, diagram, infographic, image, sketch or illustration. More than just transferring information, knowledge visualization attempts to ensure students receiving this visual information understand greater insights and perspectives surrounding a given topic.

c) Internet Use Behavior (IUB)

Internet Use Behavior (IUB) is the Internet activities or actions of users when browsing and can be observed through the which type of website or online activities. Online Activity means online forms of communication including email, text, online files, social media, pictures and videos that can be shared via websites, apps, and/or through social networking platforms. In this study, the term IUB refers to Internet online activities that has been utilized by the students.

d) Student Performance

The student performance involves factors such as the intellectual level, personality, motivation, skills, interests, study habits, self-esteem or the teacher-student relationship. In this study, students' academic performance is measured by the Cumulative Grade Point Average (CGPA). CGPA calculates the overall average of students' academic performance for all examinations' grade for all semesters during the tenure years in the college or university.

e) Cognitive

The Meriam-Webster dictionary defines the cognitive skills and knowledge involve the ability to acquire factual information, often the kind of knowledge that can easily be tested. It also involving conscious intellectual activity (such as thinking, reasoning, or remembering). However, based on Cavanagh et al. (2010) defines the cognitive which sees thinking as the manipulation of an internal representation (“Mental Model”) of an external domain. In this study, the term cognitive refers on the level of users understanding through the use of visualization.

f) Reasoning

As described in Oxford dictionary, reasoning is the action of thinking about something in a logical and in sensible way. Reasoning is the working through of problems so that one can explain either why something happened or what will happen. In this study, reasoning is defined as the drawing of inferences or conclusions through the use of visualization.

g) Knowledge-Base

In general, a knowledge base is a centralized repository of information. A public library, a database of related information about a particular subject and whatis.com could all be considered examples of knowledge bases. In relation to this study, a knowledge base is a machine-readable resource for the dissemination of information, generally online and it is an integral component of knowledge management systems. They are used to optimize information collection and information organization and retrieval.

h) Real-Time

A term used to describe computer systems that update information at the same rate as they receive data. In this study, the term real-time is one of the elements used to measure the PKVS prototype based on how the prototype able to deliver live data, relevant data and real-time data to support decision making process.

1.9 Organizations of Chapters in Thesis

This thesis consists of seven chapters. Chapter 1 is the introduction part that gives a general overview of the study. This chapter comprises of background of the study, problem statement, research questions and objectives, scope, significance of the study, research frameworks, and definition of terminologies. Chapter 2 presents the literature review of all concepts and issues related to the study. This chapter covers the topic of Knowledge Visualization, Prescriptive analytic in Big Data, Overview of student performance and Internet use behavior in IHLs, and overview of related Theories and Models. Chapter 3 outlines the research methodology that consists of Research Method, Research Design, as well as the steps of the research method, research sampling and the instruments. In Chapter 4, the model development is presented. Prototype Development that was undertaken by implementing the proposed model is describe in Chapter 5. Next, Chapter 6 presents the three stages of evaluation consisting of Model Verification, Usability Testing results, and Model Validation. Chapter 7 discusses on the results and presents new findings based on the research questions. The research contribution, directions for future research, and conclusion of the thesis are also included in this chapter. The chapter ends with a discussion on the limitation of the study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter discusses related the works and foundations of this study. The review focuses on the Knowledge Visualizations (KV) of Internet usage on students' performance to identify the gaps and understand the implications for proposing an Institutions of Higher Learning (IHL) KV model. The concepts of Big Data and visualization, which are closely linked are discussed in Section 2.2. The history of KV is described in detail starting from Data Visualization (DV) and Information Visualization (InfoVis) in Section 2.3. The highlight is on how KV can support learning and understanding, especially in education. This section also captures the concepts of cognitive and reasoning to support the success of KV. The visual analytics and cognitive components are included in Section 2.4. Section 2.5 provides extensive reviews an analytics technique that have been applied in IHL including the prescriptive analytic approaches. In section 2.6 studies on decision making process in IHL, whilst Sections 2.7 and 2.8 present the reviews related to the IHLs' student performance and Internet usage. The related theories on prescriptive knowledge visualization are analyzed Section 2.9. Finally, Section 2.10 concludes this chapter.

2.2 Big Data and Visualization

The term Big Data is now a hot topic and often covered in the field industrial IT (Information Technology). Big data recently emerged as a new research field called Big Data Science (Hossein Motlagh, Mohammadrezaei, Hunt, & Zakeri, 2020) and Big Data Analytics comes as a promising methodology to retrieve knowledge from the massive data (Garcia-Arroyo, & Osca, 2021; Sanjay & Alamma, 2016). With

almost everything available online nowadays, organizations look at the Big Data collected to gain insights to improve their services and profit purposes (Ahmed et al., 2017). The use of Big Data techniques has the potential to help organizations to improve operations and make faster and smarter decisions.

The concept of Big Data has been around for many years. Currently, almost all organizations recognized the importance of applying the analytics approach to analyze the large data sets that flow into their business in providing valuable information (Raghupathi & Zhou, 2019). Previously, businesses in the 1950s, had already used the conventional analysis by using spreadsheets to manually examine a large amount of data to uncover valuable information and trends. Eventually, Big Data Analytics gave a great amenity as compared to the conventional analysis, in terms of speed and efficiency (Roy, Rautaray, & Pandey, 2018).

In addition to these properties, there are three stages required to unlock the value of Big Data in any organization. These include data collection, analysis, and visualization. Data collection is the first step in unlocking the value accrued from Big Data. This requires identifying data that can reveal useful and valuable information. Data must be filtered for relevance and stored in a form that is useful, as little is gained in investing in huge amounts of data and storage infrastructure if the vast majority of the data in it is not usable. Once rendered into a usable form, the data have to be analyzed to generate actionable information. Nevertheless, with the growing diversity in the nature of data, the management and analysis of the diverse data sets involve a very complex process. Therefore, the analysis should include the linking and connecting of various correlating data sets to be able to grasp and convey valuable information. This situation is termed as the 'complexity' of Big Data. Finally, in the last stage, data visualization, the analyzed data will be presented in an

interpretable form and can be integrated into existing processes, which will facilitate decision-making.

Big Data and visualizations are two terms that are related and used interchangeably (Po, Bikakis, Desimoni, & Papastefanatos, 2020; Peddoju, & Upadhyay, 2020). In some cases, these terms are used to describe an evolutionary stage in the analytic concepts that are used to support organizational decision-making. In the world of Big Data, data visualization tools and technologies are essential to analyze massive amounts of information and make data-driven decisions (Medeiros, & Macada, 2022). By using visual elements, such as charts, graphs, and maps, data visualization tools provide an accessible way to see and understand trends, outliers, and patterns in data (Emmanuel & Stanier, 2016). Visualization is a key tool to make sense of the trillions of rows of data generated every day. Data visualization combines, organizes, and integrates various data sources into comprehensible versions of information by highlighting the trends and outliers (Endert et al., 2017). A good visualization tells a story, removing noise and extracting useful information. Effective data visualization is a delicate balancing act between form and function (Suwignyo, Kurniawan, Kuswandi, & Ariani, 2022). The data and the visuals need to work hand in hand to combine great analysis with great storytelling.

In recent years, an enormous amount of data is generated from different sectors, such as mHealth, education, e-commerce, and the applications of Smart City (Islam, Razzaque, Hassan, Nagy, & Song, 2017). For example, 2.5 quintillion bytes of data was generated in 2015. Moreover, the data creation speed is increasing rapidly. For instance, in 2018, the data generation speed was at 50,000 GB/day, while in 1992, 100GB/day (Oppitz, & Tomsu, 2018; Arafat et al., 2017). However, this huge amount of information is not going to be beneficial until the organizations obtain some

insights from the data (Chawla, Bamal, & Khatana, 2018). During the era of Big Data, data visualization has become a fascinating area with the challenge of representing large volumes of data. As for the Data Scientists, their final work should include the following; results of analyses, statistical design, computational algorithms, history of data, prophecies, and predictions (Cheney-Lippold, 2017). The data visualization techniques enable data scientists to present information in interactive and visual formats that are more attractive and comprehensible to human.

Data visualization offers several important advantages. It enables you to quickly process complex information so that you can understand key information (Ware, 2019). Moreover, you are no longer required to employ conventional spreadsheets, which frequently lacked crucial insights. The best about data visualization tools, it can lead you to better business decisions and actionable insights (Solis, 2019). Therefore, you can quickly identify the area that needs improvement to enhance productivity, increase sales, and grow your company. Data visualization and analytics are nowadays one of the cornerstones of Data Science, turning the abundance of Big Data being produced through modern systems into actionable knowledge (Polonsky et al., 2019). Data visualization tools help you to easily understand complex information by representing data through graphs or charts, whereas data analytics simplifies the process of analysis to help you make more informed business decisions (Islam, & Jin, 2019). Indeed, the Big Data era has realized the availability of voluminous datasets that are dynamic, noisy and heterogeneous in nature. Transforming a data-curious user into someone who can access and analyze that data is even more burdensome now for a great number of users with little or no support and expertise on the data processing part. Thus, the area of data visualization and analysis has gained great attention recently, calling for

joint action from different research areas from the Information Visualization, Knowledge Visualization, Human-Computer Interaction, Machine Learning, Data management & Mining, and Computer Graphics. Based on these reviews, there seems to be a need for expanding these study to show how the integration of data visualization and data analytic can be used to solve decision making issue. Therefore, the aim of this paper is to apply the big data visualization concept as the foundation to design prescriptive analytic models in supporting decision-makers to improve students' performance in higher educational institutions. Next section will explain in details the four of hierarchy of visualization which are Data Visualization (DV), Information Visualization (InfoVis), Knowledge Visualization (KV) and Wisdom Visualization (WV).

2.3 Visualization

Visualization means to imagine and describe something in a visual format. Visualization skills are related to the Jean Piaget theory of cognitive and intellectual development (McLeod, 2018). Tufte (2001) defined visualization as the descriptions of information that can be obtained in the pictures, tables, diagrams, and graphs, which are complete, systematic, and focused. As for Tartre (1990), visualization skills signify a way of developing new thinking in which information will be associated with the structure of prior knowledge to help a person understands something new.

Visualization led to the construction of what is seen and perceived in the active mind and thus, forms a framework to evaluate the resulting image through a process of observation. Human perception plays an important role in visualization. An understanding of perception can significantly improve both the quality and quantity

of information being displayed (Khulusi et al., 2020). This is supported by Janjevic & Winkenbach (2021), who defined visualization in a wider context of building and redoing the image of an object or phenomenon in the mind without seeing it.

The concepts of data, information, and knowledge (Figure 2.1) are fundamental in all kinds of visualization. There have been numerous attempts to define the terms "data", "information", and "knowledge".

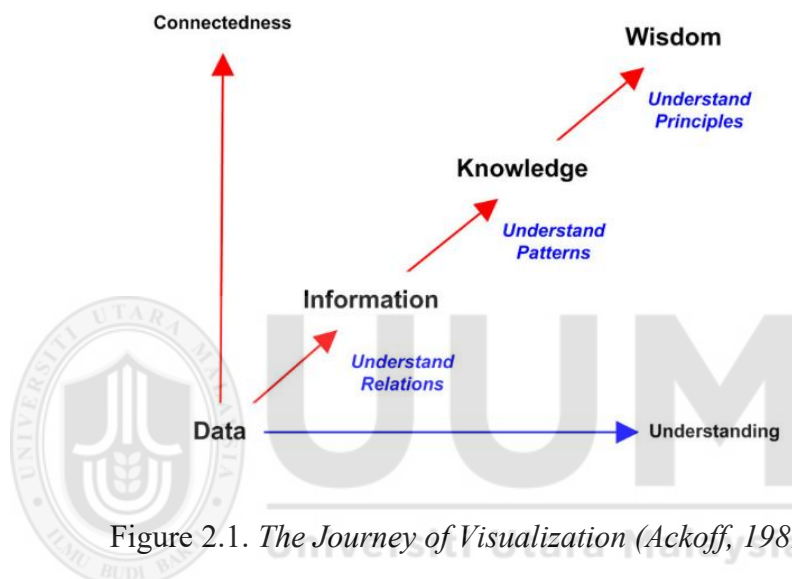


Figure 2.1. *The Journey of Visualization (Ackoff, 1989)*

From Figure 2.1, data represents raw facts. Data include symbols and isolated or non-interpreted facts. Data represent a fact or statement of event without any relation to other data. Data simply exists and has no significance beyond its existence (in and of itself). It can exist in any form, usable, or not. It does not have meaning of itself. In visualization, data, information, and knowledge are three terms being used extensively, often in an interrelated context. In many cases, they are used to indicate different levels of abstraction, understanding, or truthfulness. For example, ‘visualization is concerned with exploring data and information (Janicke, Wiebel, Scheuermann, & Kollmann, 2007); ‘the primary objective in data visualization is to gain insight into an information space’, whilst ‘information visualization’ is for ‘data mining and knowledge discovery’

(Amar, & Stasko, 2005). In other cases, these three terms are used to indicate data types. For instance, as adnominal in noun phrases, such as data visualization, information visualization, and knowledge visualization. These examples suggest that data, information, and knowledge could be both the input and output of a visualization process, raising questions about the exact role of data, information, and knowledge in visualization. Although both are developed by their own capabilities to promote visual expression effectively, the utilization the knowledge and information visualizations in various research areas differs accordingly. Chen et al. (2008) compared data, information, and knowledge visualizations from four aspects; objects, purpose, ways and interactive types, as shown in Table 2.1.

Table 2.1.
Comparison of Data Visualization Information Visualization and Knowledge Visualization

	Data Visualization	Information Visualization	Knowledge Visualization
Visualization objects	Spatial Data	Non-spatial Data	Human knowledge
Visualization Purpose	Representation abstract data in intuitive way	Find new information from abstract data	Promote dissemination and innovation of group knowledge
Visualization ways	Computer graphics, image	Computer graphics, image	Drawing sketches, knowledge chart, visual metaphors etc.
Interactive types	Human-machine interaction	Human-machine interaction	Human-human interaction

Based on the comparison in Table 2.1, all the concepts of DV, InfoVis and KV are applied in this study. This study attempts to convert data to knowledge through the analytic and visualization process. The Internet usage data are transformed into a usage pattern to indicate the impact of Internet on the students' academic performance. From the analysis results, knowledge is obtained in the form of knowledge-based to expand the cognitive skills. Knowledge-based, which are produced based on human knowledge, will be transformed into knowledge charts or any kind of visual metaphors to help decision maker make decision based on the graphical results.

2.3.1 Data Visualization

Visual representation of data has evolved rapidly in recent years. In the DIKW hierarchy, visualization starts with data. Referring to Bellinger, Castro, and Mills (2004), the continuum starts with raw data, "it's simply exists and has no significance meaning beyond its existence. It exists in any form, usable or not". Card (1999) defined it as "Visual representation of computer- supported, interactive, used to extract abstract data and to expand the cognitive". Data Visualization on two- or three-dimensional structures has been made before computers are used to create visualization. In his book, Edward R. Tufte provides some examples of visualization techniques that have been used for several years (Kanegaonkar, Kashikar, & Waykar, 2021). Since the computer is used to create visualization, many visualization techniques are developed and enhanced to process a large amount of data and display them interactively. Data do not have the mapping standards with the Cartesian coordinate system because they are no longer in the form of two or three dimensions. In general, relational databases can represent a set of multidimensional data, where the attributes are related to the dimensions of that database.

In this study, data from students' Internet usage behavior are collected in the form of an Excel file. The students' Access Log, which records all their Internet browsing activities contains the volume, type, hours, date and time, bandwidth (in and out), and number of connections in a day of Internet browsing. These influencing aspects are considered as input variables that have no meaning before transforming them into information. Yet, this is not the final outcome, instead these data have to be conceived as transformation processes within the DIK continuum. Based on DVs' limitation, then InfoVis are introduced to overcome the limitation.

2.3.2 Information Visualization

When dealing with large amount of diverse information, making sense of all this information is a challenging process. The challenge of InfoVis is to regularly provide visual representations of large datasets (Earnshaw, Dill, Kasik, & Earnshaw, 2019). It involves the sense making process in finding meaning from the data itself. Information visualization is a part of an overall visualization field that incorporates both the information and scientific visualization (Chefer, Gur, & Wolf, 2021). Information visualization requires mapping data in a visual or occasionally auditory format for users, which can them to explore information and visual information search (Liu et al., 2021).

InfoVis consist of visualization and distortion techniques (Keim, 2002). These techniques are expected to be mapped with the nature of the data to be visualized (Golfarelli, & Rizzi, 2020) and aligned with the explicit knowledge preferences of the decision-makers' domain. This is essential to ensure InfoVis supports the decision-making process (Graf, Graf-Drasch, Tiefenbeck, Weitzel, & Fridgen, 2020). The choice of appropriate InfoVis' technique is to achieve undistorted information representation (Schottler, Yang, Pfister, & Bach, 2021). Therefore, choosing the

most suitable visualization technique is the key in presenting the information that supports a decision-making process. The interaction and distortion techniques aid the exploratory activities and control, which will enhance users' experience. However, there is need to analyze each of the InfoVis techniques to determine the suitability in the representation and presentation of the IHL's decision-makers' explicit knowledge preferences. Then the KV is introduced to make sense of data and convert an information to knowledge.

2.3.3 Knowledge Visualization

The new direction on visualization, well known as Knowledge Visualization was introduced by Remo Aslak Burkhard and Meier (2005). Knowledge visualization examines the use of visual representations to improve the creation and transfer of knowledge between at least two people. It is also defined as the use of all the graphic means to construct and convey complex insights (Shen et al., 2019). According to Keller and Tergan (2005), knowledge is information, which has been cognitively processed and integrated into an existing human knowledge structure that emerges when different information is combined to accomplish a specific task. Visualization techniques are powerful tools that are frequently employed in knowledge discovery processes.

Jonassen (1991) and Jonassen et al. (1993) have described a variety of methods for fostering spatial learning strategies and technologies used for the visualization of knowledge. The most often used methods are mind and concept mapping. Mind maps were suggested as a spatial strategy that uses only key words and images to aid students in structuring ideas and taking notes (Buzan, 1995). Visualizations of knowledge based on the mapping technology concept may be used for mapping, managing, and manipulating conceptual knowledge (Canas, Leake & Wilson, 1999).

The conceptual model for implementing the digital concept maps as tools for managing knowledge and information resources was outlined by Tergan (2003).

According to Donnell, Dansereau, and Hall (2002), the concept of "knowledge visualization" is restricted to the externalization aspects of knowledge by an individual in a "freestyle mapping mode". In literature, the term "knowledge visualization" will also be used if a knowledge structure of an expert is presented to students as a means for self-assessing knowledge and aiding comprehension and navigation. Up to now, "knowledge visualization" has been focusing on the conceptual knowledge structures. In the educational context, knowledge visualization methods have been used for fostering idea generation, learning, assessment, and instruction. Reviews on the effectiveness of the mapping concept have been published by Bruillard and Baron (2000), Jonassen et al. (1993), and O'Donnell, Dansereau, and Hall (2002). The results of empirical research provide evidence that concept mapping bears a high potential in fostering "external cognition" (Scaife & Rogers, 1996) depending on the task requirements, the domain knowledge of the users, and their spatial learning literacy.

The use of KV in the learning environment is an effective way to reconstruct the learning element in student's cognitive experience because it can influence the factors of learning through three attributes; cognitive engagement, interactivity, and multimedia learning (Gilbert, 2005). Three factors that can affect learning are cognitive engagement, multimedia learning, and interactivity (Yusoff, Katmon, Ahmad, & Miswan, 2013).

Although several studies on DV and InfoVis in higher educational institutions have been conducted, the effectiveness of the visualization system is still an open area to

be explored. Hence, this study proposes a holistic approach of visualizing the data in higher education environment. The KV technique generates knowledge using an analytic approach by incorporating cognitive and reasoning elements, which were visualized in the form of a dashboard are discovered in this study. In the next section will discussed about visual analytics which involve cognitive and reasoning elements that will applied in this study.

2.4 Visual Analytics

Visual analytics is the science of analytical reasoning supported by interactive visual interfaces (Keim et al., 2008; Thomas & Cook, 2005). It is an emerging discipline, combining several high-level concepts, such as data analysis, visualization, human user, and interaction techniques, targeting the discovery of insights into large data sets and databases (Rodrigues, Burch, Silvestro, & Weiskopf, 2017). Over the last decades, data was produced at an incredible rate. However, the ability to collect and store this data is increasing at a faster rate than the ability to analyze it. While purely automatic or visual analysis methods were developed in the last decades, the complex nature of many problems makes it indispensable to include humans at an early stage in the data analysis process. Visual analytics methods allow decision-makers to combine their flexibility, creativity, and background knowledge with the enormous storage and processing capacities of today's computers to gain insight into complex problems (Gelder, Kruger, & Thomman, 2020). Thus, the goal of visual analytics research is to turn the information overload into an opportunity by enabling decision-makers to examine massive, multi-dimensional, and multi-source data (Ihm, Lee, & Park, 2020). The study, focus is on visual analytics by integrating the cognitive and reasoning elements to guide the development of new methods for evaluating specific aspects of the visualization.

2.4.1 Visual and Cognitive Analytics

Cognitive effort, defined as the total amount of cognitive resources needed to complete a task, comprised of cognitive resources of perception, memory, and judgment (Cooper-Martin, 1994; Russo & Doshier, 1983). The cognitive efforts, which involves human participation from various levels of thinking functions as a tool to leverage a decision-making process. The effort also utilized the bottom-up method of visualization to process and transform data into meaningful information. The role of visualization is to leverage the function of a human visual system as an effort to provide insight from abstract information (Hearst, 2009).

Based on the related literature review, it was found that most of the researchers have focused on the visualization and role of cognitive process. For instance, Patterson (2014) had developed the human cognition framework for visualizing information visualization by emphasizing on the top-down cognitive processing method that enables the induction of insight, reasoning, and understanding. The discussion of the framework focuses on the way the bottom-up information is processed to activate an organized knowledge structure represented in long-term memory. A critical part of those systems is the data representation component of the visually intensive applications, such as dashboards and data visualization (Hovis, 2002).

In another research, Mnguni (2014) developed a model to examine visual literacy within science education empirically. The researcher explored various theories related to the cognitive process of visualization from different domains. Among the critical aspects of the discussion include the construction of knowledge using visual models and related theories. The knowledge construction, adopted from Mayer (2002), was based on the cognitive theory of multimedia learning, which relates to the constructivist epistemology of learning. According to Mayer (2003), the

visualization process of learning consists of three stages; comprehension of visual information, processing of this information into cognitive structures, and externalization of information as visual models. Visualization enables the selection and effectiveness of using a set of cognitive skills for perceiving, processing, and producing visual models.

While discussing the theoretical cognitive process in visualization based on the interaction of two domains, cognitivism and constructivism, three categories were identified, which are Internalization Visual Model (IVM), Externalization Visual Models (EVM), and Conceptualization Visual Models (CVM). Eventually, the author concluded that visualization is not a linear process. Visualization represents an occurrence of various interconnected actions, which are driven by the need to generate knowledge. The interconnections depend on prior knowledge, which is used to construct new knowledge. Therefore, this study attempts to add the element of cognitive analytics into the existing model to produce better solution and recommendation for decision-makers. These would enhance the KV of Internet usage to improve students' academic performance in IHL.

2.4.2 Visual and Reasoning Analytics

The role of visual analytics in transforming data into knowledge is well known among researchers. Even though the technique has successfully involved human participation, visual analytics failed to add the understanding from the analyses (Green & Maciejewski, 2013). Thus, a complete study of visual analytics not only requires a computational method but also an understanding on the rationale of the analyzed results. The reasoning or rationale can be determined between single or multiple users and visualizations collaboration.

In reality, even though computer is powerful in analyzing data, however, a computer cannot adjust the results according to a user's understanding. Hence, the user is expected to adapt to the visualized analysis. Even though the technique has successfully involved human participation, visual analytics failed to add the understanding from the analyses (Green & Maciejewski, 2013). This indicates that the computational solution lacks human insight and reasoning process (Quinn & Bederson, 2011). Reasoning has the ability to make sense of information, create mental models, adapt to rapid changes, generate hypotheses, and defend conclusions drawn with evidence (Klaczynski, 2001; Neys, 2006). These processes are currently outside the purview of computational analyses and can only be done by a human analyst. Although visual and reasoning analytics differ, they need each other to complete visualization models.

Richard et al (2011) introduced Pair Analytics, a method for capturing reasoning processes in visual analytics. They claimed that Pair Analytics offers two advantages; (i) as a natural way of capturing reasoning processes and (ii) an approach to capture social and cognitive processes used to conduct collaborative analysis in real-life settings. A method that allows the capturing and conceptualizing an analyst's reasoning processes is required to create knowledge and models involving a cognitive process in visual analytics. Based on those reasoning ability characteristics, this study utilizes the reasoning analytic in a visual analytic process to develop prescriptive analytic model of student performance for decision-making process. Next section will explain in details analytics approaches that has been used in IHL.

2.5 Analytics in Institution of Higher Learning (IHL)

Big Data is a knowledge system that is already changing the objects of knowledge and social theory in many fields while also having the potential to transform management decision-making theory (Boyd & Crawford, 2012). Big Data incorporates the emergent research field of learning analytics (Long & Siemen, 2011), which is already a growing area in education. However, research in learning analytics has largely been limited to examining indicators of individual student and class performance. Big Data brings new opportunities and challenges for institutions of higher education. Long and Siemen (2011) indicated that Big Data presents the most dramatic framework in efficiently utilizing the vast array of data and ultimately shaping the future of higher education. The application of Big Data in higher education was also echoed by Wagner and Ice (2012), who noted that technological developments have certainly served as catalysts for the move towards the growth of analytics in higher education.

In the context of higher education, Big Data connotes the interpretation of the processes of gathering a wide range of administrative and operational data aimed at assessing institutional performance and progress in predicting future accomplishments and identifying potential issues related to academic programmed, research, teaching, and learning (Hrabowski, Suess, & Fritz, 2011a, 2011b; Picciano, 2012). To meet the demands of improved productivity, higher education must bring the analytics tool into the system. As an emerging field in education, the Big Data framework is deemed as appropriate among a number of scholars in addressing some of the key challenges currently faced by IHLs (Long & Siemens, 2011). At this early stage, much of the work on analytics concerning higher education comes from interdisciplinary research, comprising various fields, such as Educational

Technology, Statistics, Mathematics, Computer Science, and Information Science. The core element of the current work on analytics in education centered on data mining.

Big Data in higher education also covers database systems that store large quantities of longitudinal students' data right down to very specific transactions and activities on learning and teaching. During their interaction with learning technologies, students usually leave behind data trails that can reveal their sentiments, social connections, intentions, and goals. Therefore, researchers can use such data to examine patterns of student performance over time, for example, from one semester or year to another.

On a higher level, the added value of Big Data refers to the ability to identify useful data and turn it into usable information by identifying patterns and their deviations. Moreover, a suggestion was made by OECD (2013), in which Big Data can be the foundation for higher education to reinvent its business model and bring together the evidence to assist in decision-making.

From an organizational learning perspective, institutional effectiveness and change adaptation rely on the analysis of appropriate data (Rowley, 1998). Hence, today's technologies should enable institutions to gain insights from data with better levels of sophistication, speed, and accuracy (Jacqueline, 2012). As technologies continue to penetrate all facets of higher education, valuable information is not only being generated by students but also by various computer applications and systems (Hrabowski & Suess, 2010).

Furthermore, Big Data Analytics can be applied to examine a student's entry on a course assessment, discussion board entries, blog or wiki activity, which generates

thousands of transactions based on student and course. These data would be collected in real or near real time as it is transacted and analyzed to suggest courses of action. This is evident in the indication made by Siemens (2011) that “[learning] analytics are a foundational tool for informed change in education”, which form understanding and make informed (rather than instinctive) decisions.

With large volumes of student information, including enrollment, academic, and disciplinary records, IHLs have the data sets needed to benefit from targeted analytics. Big Data and analytics in higher education can be transformative, altering the existing processes of administration, teaching, learning, and other academic activities (Baer & Campbell, 2011), as well as contributing towards policy and practice outcomes and addressing contemporary challenges.

Big Data can provide various predictive tools to IHLs to improve the learning outcomes of individual students and ensure a high-quality standard of academic programs. By designing a program that collects data at each level of a student’s learning processes, universities can address his/her needs by customizing the respective modules, assignments, feedbacks, and learning trees in the curriculum to promote better and richer learning.

IHLs can utilize the Big Data tools to analyze students’ performance and skill levels and create a personalized learning experience that fulfills their specific learning pathways. If used effectively, Big Data can help institutions to enhance students’ learning experience and improve their performance across the board, reducing the dropout rates and increasing the graduation numbers. Three types of Big Data analytics are descriptive, predictive, and prescriptive. In this study, all the three analytics types are applied step by step to produce best recommendations and

solution in improving students' performance based on their IUB. This will help decision-makers to be more proactive in ensuring students' success.

2.5.1 Descriptive Analytics

Descriptive Analytics focuses on presenting an overview of the collected data. An example of descriptive analytics is Google Analytics. In Google Analytics, examples of simple information include the number of visitors at a time and pages that are most visited. Simple analytics consists of summaries and averages without requiring machine learning. Descriptive Analytics does not make any prediction on the next page to be visited or reason of visiting. This type of analytics is the most commonly found. Although the simple analytics did not use machine learning processing, such data is needed, especially in benchmarking, to determine the effect of the changes we make.

Descriptive analytics in IHLs aims at describing and analyzing historical data related to students, teaching, research, policies, and other administrative processes. The goal is to identify patterns from the samples to report on the current trends of students' enrollment, graduation rates, and progress. Descriptive analytics also provides an opportunity to analyze transactional and interactional data about teaching, learning, and research to identify visible trends and patterns on current and future issues. Specifically, with descriptive analytics, institutions can investigate data within the learning management systems by looking into the frequency of logins, page views, course completion rates, and most visited content. The following section will explain on the predictive analytic technique.

2.5.2 Predictive Analytics

Predictive Analytics provides predicted results on specific outcomes. An example of predictive analytics is the recommended system of Amazon's e-commerce site. This system can anticipate the item that a buyer is interested in purchasing. This type of analytics requires machine learning to interpret the collected data. Predictive Analytics is somewhat higher than descriptive analytics because the process is more complex and complicated. Nonetheless, descriptive analytics is still required as a benchmark.

Predictive analytics provides better decisions and actionable insights based on data. The aim of predictive analytics is to estimate the likelihood of future events by determining trends, associations on related issues, and risks or opportunities. Predictive analytics could reveal hidden relationships in data that might not be apparent with descriptive models, such as demographics and completion rates. Next section will discussed the previous studies that has been using descriptive and predictive analytics in IHL.

2.5.2.1 Review of Past Studies on Descriptive and Predictive Analytics in IHL

IHLs are one of the leading users for decision making process. This is evident in series of studies conducted to attend to varieties of issues in IHLs. The use of descriptive and predictive analytics in higher education research has gained significant attention in recent years. Researchers have conducted various studies to determine student performance using these analytical techniques. Table 2.2 that summarizes the analytics techniques and data sets that have been applied by various IHLs in determining students' academic performance.

Table 2.2.
Summary of Past Studies on Student Performance

No.	Authors	Analytic Techniques	Data Set
1.	Mushtaq& Khan (2012)	Descriptive Analytics	Private colleges in Rawalpindi and Islamabad
2.	Ogedebe (2012)	Descriptive Analytics	Frequency of Internet usage, frequently browsed websites, students' performance
3.	Atchley, Wingenbach, , & Akers (2013)	Descriptive Analytics	Students of Southwest United States University
4.	Ali et al. (2013)	Descriptive Analytics	Students of Islamia University of Bahawalpur Rahim Yar Khan Campus.
5.	Sian, Yamin, & Ishak (2013).	Descriptive Analytics	Frequency of Internet use, amount of time spent on Internet, most frequent Internet access point, purposes of browsing the Internet, Internet services, problems encountered while using the Internet, influence on academic efficiency, and satisfaction with Internet facilities.
6.	Alqahtani & Mohammad (2015)	Descriptive Analytics	m-learner performance, m-learner satisfaction, m-learner motivation, m-learner behavior, perceived usefulness, content quality, ease of use, and layout/graphic design.
7.	Jaggars & Xu (2016)	Descriptive Analytics	Academic subjects offered online

8.	Shaukat et al. (2016)	Descriptive Analytics	Five public schools located in the district of Lahore Sex Distribution of Students Frequency of Internet Use Most frequent Preferred Location of Internet Usage
9.	Emeka & Nyeche (2016)	Descriptive Analytics	Purpose for Browsing the Internet Most Used Internet Service Problems Encountered in the Use of Internet Services
10.	Kabakchieva (2012)	Predictive Analytics	Students' Personal, Pre-University, and University data Students' grade in senior secondary exam, living location, medium of teaching, mother's qualification, students' other habits, family annual income, and student's family status
11.	Agrawal & Mavani (2015)	Predictive Analytics	Course, Student, and course instructor data.
12.	Sweeney et al. (2016)	Predictive Analytics	Information Technology and Engineering University of Pakistan.
13.	Asif et al. (2017)	Predictive Analytics	Students' online learning behavior (preparation, progress, resource learning, forum interaction, test)
14.	Zhang et al. (2017)	Predictive Analytics	Students' learning activities
15.	Sahebi & Brusilovsky (2018)	Predictive Analytics	XuetangX for KDD CUP 2015
16.	Qiu et al. (2018)	Predictive Analytics	Moodle Database of Madrid Open University
17.	Burgos et al. (2018)	Predictive Analytics	The University of West Scotland.
18.	Adejo & Connolly (2018)	Predictive Analytics	

19.	Yang & Li (2018)	Predictive Analytics	Student attributes (name, age, previous results, family income, previous grade)
20.	Kim, Vizitei, & Ganapathi (2018)	Predictive Analytics	Students' activity – student's curriculum program.
21.	Tripathi, Yadav, & Rajan, (2019)	Predictive Analytics	Students', teachers' and courses data.
22.	Sekeroglu, Dimililer, & Tuncal (2019)	Predictive Analytics	Student Performance and Students Academic Performance
23.	Xu, Yuan, & Liu (2020)	Predictive Analytics	Students' Learning Behavior
24.	Wang et al. (2020)	Predictive Analytics	Students' behavior (books lending, card, dormitory open/close, library open/close, student achievement)
25.	Hashim, Awadh, & Hamoud (2020)	Predictive Analytics	Demographic, academic background, and behavioral
26.	Ma, Y. et al. (2020)	Predictive Analytics	Pre-course detection (students' scores, syllabus, and course records)
27.	Waheed et al. (2020)	Predictive Analytics	Open University Learning Analytics (OULA)

The overall findings based on the previous studies show that most of the above studies focused on the descriptive analytics techniques to discover the impact of various variables in improving students' performance. The descriptive analytics technique only provides answers for "what" instead of the "why" and "how" to certain problem specifications. In addition, the technique will only present the summations regarding the people or objects that have been measured. Therefore, the descriptive analytics technique is not suitable for determining the cause and effect relationships and mainly depends on the people's responses.

The other studies have used the predictive analytics technique to predict students' academic performance. The biggest challenge of this technique refers to its limited functions of forecasting (predicting) outcomes, costs, and effects. The technique tries to extrapolate the analysis of existing phenomena, policies, or other entities to predict something that has not been tried, tested, or proposed before. This technique is often more hypothetical, theoretical, or experimental. Most importantly, the technique has several shortcomings, some of which can be overcome with, for example, better specification. Based on Table 2.2, none of the previous studies has used the prescriptive analytics technique. Most of the studies ended their works by predicting the results of students' performance.

Prescriptive analytic is applied rather than theoretical. It differs from descriptive and predictive analytic in that it goes a step further, beyond identifying success or performance or outcomes, and recommends solutions or new ideas. The prescriptive analytics technique comes up with an assertion, a solution, proposal for how to address a known problem space. The technique tries to answer questions, such as "what we should do now", "how a policy should be changed or improved", "how an organization can achieve specific outcomes or meet requirements", a set of recommendations, solutions, or ideas that involve change and action. The specific terms or phrases that are often used include "can", "should", "How can we accomplish/improve/change x?", or "What should we do now about x?". This is somewhat similar to a doctor's medication prescription to a patient. By using the same concept, this study applied the three analytics techniques as described previously. Next, the prescriptive analytics is introduced in this study to prescribe the best action based on descriptive and predictive results. Specifically, the prescription

is based on the case study to improve students' academic performance based on the IUB.

2.5.3 Prescriptive Analytics

Prescriptive analytics refers to a process that generates answers on why something will happen and provides advice on what conditions will likely to happen in the future (Banerjee, Bandyopadhyay & Acharya, 2013; Bertsimas & Kallus, 2015). These capabilities are needed by top-level management in making decisions. The process of creating a system that uses prescriptive analytics is quite difficult since its algorithms should be able to overcome the weaknesses of the previous two techniques (Haas, Maglio, Selinger, & Tan, 2011). All options for decision-making should also be considered. Hence, machine learning is the definite solution to overcome the weaknesses of the previous techniques.

Gartner (2013) defines prescriptive analytics as “the combination of optimization, rules, and data that enhances analytics by suggesting the optimal way to handle a future situation and can be applied to strategic, tactical, and operational decisions.” In other words, while the other two approaches aim to improve decision making, prescriptive analytics recommends (i.e. “prescribes”) the best path (Von Bischhoffshausen, Paatsch, Reuter, Satzger, & Fromm, 2015; Song et al. 2014). Prescriptive represents the final stage in big data analytics, which uses optimization and other mathematical models to identify the best actions and decisions (Sanjay & Alamma, 2016).

The advanced analytics technique emphasizes more on decision risk reduction and less on data. Although many organizations are still moving from basic reporting to predictive analytics, the next wave of investments will be in prescriptive analytics to

improve decision making (El Morr, & Ali-Hassan, 2019). Unfortunately, analytics and simulation only will not be enough, the decision process will also have to change, in which people should learn new skills and ways to make decisions. The transformation must be organizational, as well as technological, and the change will have to come from the top.

Prescriptive analytics helps institutions of higher education to assess their current situation and make informed choices on alternative course of events based on valid and consistent predictions. It combines the analytical outcomes from both the descriptive and predictive models to assess and determine new ways in achieving desirable outcomes while balancing constraints. Basu (2013) indicated that prescriptive analytics enables decision-makers to look into the future mission of critical processes, opportunities, and issues. Moreover, the best course of action is also presented. Based on the above advantages, the prescriptive analytics is worth to be applied in this study for developing a model to improve students' performance. Next will discussed in details the previous study that has been using prescriptive analytic techniques in different domain.

2.5.3.1 Previous Studies on Prescriptive Analytics Approaches

An increasing number of research have recognized the prescriptive analytics in various domain, such as in engineering (Salah, & Srinivas, 2022; McFowland, Gangarapu, Bapna, & Sun, 2021; Hoo Meng & Amalathas, 2019; Pospieszny, 2017), automation and manufacturing (Vater et al., 2019; Bousdekis, Lepenioti, Apostolou, & Mentzas, 2019; Krumeich, Werth, & Loos, 2016), logistics (Notz & Pibernik, 2022), transportation (Wang, Cheng, & Deng, 2018), healthcare (Kaur & Mann, 2017; Raghupathi, 2014) business (Ho, Hanasusanto, 2019) as well as management domain (Abdelwahed et al., 2022). In addition, a number of researchers have

conducted a Systematic Literature Review (SLR) on prescriptive analytics (Bousdekis et al, 2016; Deshpande et al., 2019). Similarly, Bawa et al. (2021) have produced another interesting study by suggesting the future direction of this technique based on literature review and discussion with experts in other domains. Collectively, all of these studies provide meaningful direction for researchers that are interested to apply this technique in different domains. In addition, other examples of prescriptive analytics technique across various domains are listed in Table 2.3.

Table 2.3.

Previous Studies using Prescriptive Analytics Technique

Domain	Author (s)
Industry 4.0 (automation and manufacturing)	Lepeniotti et al., 2020; Belov, Nikolaev, & Uzhinsky, 2020; Bousdekis et al., 2019; Krumeich, Werth, & Loos, 2016; Gupta & Maravelias, 2017; Vater et al., 2019; Jank, Dolle, & Schuh, 2019; Schuh, Prote, Busam, Lorenz, & Netland, 2019.
Business	Ho, & Hanasusanto, 2019; Greasley, 2019; Groger et al., 2014; Kawas, Squillante, Subramanian, & Varshney, 2013
Management	Kiaghadi, & Hoseinpour, 2023; Brandt, Dlugosch, Abdelwahed, van den Berg, & Neumann, 2022; Notz & Pibernik, 2021; De Leoni, Dees, & Reulink, 2020; Berk, Bertsimas, Weinstein, & Yan, 2019.
Transportation	Tinoco, Parente, Correia, Cortez, & Toll, 2021; Wang, Cheng, & Deng, 2018

Logistics	Soeffker, Ulmer, & Mattfeld, 2022; Grzegorowski, Janusz, Łazewski, Swiechowski, & Jankowska, 2022; Kandula, Krishnamoorthy, & Roy2021;
Engineering	Salah, & Srinivas, 2022; McFowland, Gangarapu, Bapna, & Sun, 2021; Hoo Meng & Amalathas, 2019; Pospieszny, 2017.
Healthcare	Galli, Levato, Schoen, & Tigli, 2021; Oesterreich, Fitte, Behne, & Teuteberg, 2020; Mosavi, & Santos, 2020; Lopes, Guimarães, & Santos, 2020; Kim et al., 2020; Bertsimas, Paschalidis, & Wang, 2020; Raghupathi,V., Zhou, & Raghupathi, W., 2019; Ashfaq, Nowaczyk, 2019; Goyal et al., 2016; Kaur & Mann, 2017

Table 2.3 presents a few examples of the popular domains that have utilized the prescriptive analytics technique. More research will be produced in the future since this technique is proven to be successful (Deshpande et al., 2019; Soltanpor & Sellis, 2016). This study believes that this technique can solve the issues on the impact of IUB on IHL students' performance. The next section explains the decision making process that perform in IHLs.

2.6 Previous Study on Student Performances

A performance refers to one's ability to adapt to something, understand, master and be able to apply what has been learned. According to Wikipedia, performance comes from the Dutch language which means the result of the effort. From the definition of

performances, the sense of self-esteem is the result of one's efforts. Performances can be achieved by relying on intellectual, emotional, spiritual abilities, and self-esteem in facing the situation of all aspects of life. The character of the accomplished person is to love the job, have the initiative and creativity, never give up, and carry out the task earnestly. These characters are important in order to achieve a certain achievement.

The concept of student performances in IHL refers to student achievement in the exam used to measure student performance and the level of understanding of students in a learning subject. In addition, student performance can also be measured through the involvement of students in learning activities both inside and outside the classroom. Understanding student performance cannot be separated from learning activities, because learning is a process, while learning achievement is the result of the learning process.

There are many factors that affect student performance in IHL. Among them are the teaching and learning methods used during the learning session at the school. The techniques used by lecturers to teach have great influence on student achievement in IHL. Lecturers need to identify problems faced by students during the learning session by interacting with students. In addition, lecturers need to diversify their teaching techniques so that they are not stereotypical and bore the learners.

The most frequently emphasized aspect of performance is the academic aspect of the students. Academic success has great influence on students' self-esteem, motivation, and persistence in higher education. Low academic performance or high failure rate may result in unacceptable rejection levels, reducing the number of graduates and

increasing cost of education. Therefore, academic achievement has always been a topic of interest to educators.

Academic performance has different definitions by researchers. Excellent academic achievement is the determination of one who understands the learning process. Academic performance according to Cambridge Reporter University wrote by Justice (2019) is often defined in terms of exam performance. In this academic study the performance is characterized by overall performance on a yearly basis attributable to Average Grade Value (GPA). GPA values will take into account test performance, coursework and exams. The minimum and maximum score scores are 0 (Grade F) and 4.0 (Grade A) respectively. This GPA value indicates that higher scores are the best in academic performance. Therefore, GPA will be the most important measurement in measuring the performance of a student.

Recent studies have identified a number of factors that affect students' academic performance at various educational centers. Among the factors include class attendance, age, learning style or priorities, gender, class size, admission qualification, family support, and learning infrastructure (Baashar et al., 2022; Ahmady, Khajeali, Sharifi, & Mirmoghtadaei, 2019; Bulman, & Fairlie, 2016; Ahmed, Vveinhardt & Nawaz, 2016).

A study conducted by Yeh and Cheng (2016) in Taiwan focuses on the relationship between the impact of computer games and student performance. Firstly, their findings reveal that participation in computer games negatively affects the student's academic performance. The results were also supported by other researchers who carried out similar study. However, the difference was on the sample, which involved high-level students (Hossain, 2019). Secondly, the study proposed a more flexible

strategy for parents to supervise their children while playing computer games to help achieve the best academic decisions.

Students' participation in co-curricular activities were also evaluated to determine its effect on academic performance. The results show that such involvement does not drop the students' CGPA scores (Jayanthi, Balakrishnan, Ching, Latiff, & Nasirudeen, 2014). This is also reinforced by Mohamed Nafuri et al. (2022), who also obtained positive results. According to Hossan, Khan and Hasan, (2021), participation in co-curricular activities can also be positively associated with the success of education for young people.

However, some of the previous studies acquired different results when examining the correlation between technological impact and student performance. The high-level students were more likely to use the technology and Internet to communicate with friends and family members. The students primarily use the Internet for interpersonal communication through e-mails, instant messages, and chat programs (Ozdamli, & Ercag, 2021; Pagliaro, 2020). While most people agree that using the Internet is a healthy productive activity whereby students can pursue opportunities by surfing the web and engaging in chat rooms (Sari, 2020), many students have had a negative impact on their academic performance due to internet addiction (Abbasi, Jagaveeran, Goh, & Tariq, 2021; Azizi, Soroush, & Khatony, 2019).

However, a study conducted by Usman, Alavi, and Syafiq (2014) found no significant relationship between Internet addiction and academic achievement. This denotes that the effect of Internet addiction on student's academic performance was not at a critical level. Therefore, students should be aware of the negative effects Internet usage. At the same time, early prevention measures have to be devised.

Many studies have claimed that extreme or dubious Internet can cause harmful effects on individuals, academic problems, and changes in social behavior, habits and abilities in a negative way. Therefore, the impact of internet use on students' performance should be further studied.

2.6.1 The Impact of Decision-making Process Towards Student Performance in IHL.

In Institution of higher learning, student performance is the most important factor to a university's quality (Mengash, 2020). Student performance has a significant impact on decision-making in institutions of higher learning (IHL) (Xiao et al., 2022). The performance of students can influence various aspects of decision-making, including academic policies, program development, resource allocation, and student support services. Here are some key ways in which student performance can impact decision-making in IHL:

1) Curriculum and Program Development: Student performance data, including grades, course completion rates, and feedback, provide valuable insights for curriculum and program development. Low student performance in specific courses or programs may prompt IHLs to review and revise curriculum content, teaching methodologies, or assessment strategies to better align with student needs and improve learning outcomes (Namoun, & Alshanqiti, 2020, Schildkamp, 2019).

2) Student Support and Interventions: Student performance data can help identify students who may be struggling academically or at risk of not meeting their educational goals. IHLs can use this information to implement targeted interventions such as academic advising, tutoring services, mentoring programs, or academic support initiatives. Decision-makers can allocate resources and design support

programs based on student performance data to improve retention, graduation rates, and overall student success (Nabil, Seyam, & Abou-Elfetouh, 2021).

3) Resource Allocation: Student performance data can influence resource allocation decisions within IHLs. High-performing programs or departments may receive additional resources, funding, or faculty appointments to maintain their quality and further enhance student outcomes. Conversely, programs with consistently low student performance may prompt administrators to evaluate resource allocation or consider modifications to ensure appropriate support and improvement (Fauzi et al., 2019).

4) Accreditation and Quality Assurance: Accrediting bodies and quality assurance agencies often consider student performance metrics as part of the evaluation and accreditation process for IHLs. Institutions with strong student performance indicators are more likely to receive positive evaluations, recognition, and accreditation. Therefore, decision-makers in IHLs pay attention to student performance data to meet accreditation standards and maintain institutional reputation (Nujid, & Tholibon, 2022; Nkala, & Ncube, 2020; Dei, 2019; Nieto-Chaupis, 2017).

5) Institutional Research and Planning: Student performance data is crucial for institutional research and planning purposes. Decision-makers use these data to analyze trends, monitor academic progress, and assess the effectiveness of policies and initiatives. By examining student performance, IHLs can identify areas of improvement, set goals, and develop strategic plans to enhance overall educational quality (Afida, 2022).

It is important to note that decision-making in IHLs is typically a complex process that considers multiple factors beyond student performance alone. Stakeholder input, external factors, institutional goals, and legal requirements also play significant roles in shaping decision-making processes. Ultimately, the goal is to utilize student performance data in a comprehensive manner to inform evidence-based decision-making that promotes student success, improves educational outcomes, and supports the overall mission of the IHL. Next section will explain on the utilization of Internet towards students performance.

2.7 Internet for Educated People

The use of the Internet has increased drastically throughout the world, mainly due to the wide range of available applications. Young people occupy the largest share of the benefits because they are more interested in new technologies, applications, and developments compared to the other age categories (Siddiqi & Memon, 2016). The youngsters use the Internet for various purposes, such as social relationships, academic study, work, communication, and entertainment (Kirci, 2015). Despite all the benefits, there is a group of people who are more likely to say that the Internet has negative rather than positive influences on morality (Pew Research Centre, n.d).

Kirci (2015) highlighted that the use of the Internet among youngsters (aged 16 and above) in Turkey has increased from time to time. In the early 2000s, the Internet was mainly used for educational purposes. Although the development of the Internet in Turkey started relatively late as compared to America and Europe, it does not limit the youngsters from benefiting from it, especially in the field of education.

Another study by Nachmias, Mioduser, and Shemla (1999) examined the extent and characteristics of Internet usage among 384 junior-high and high school students in

Israel. The focus was to investigate the relationship between the purpose and patterns of Internet usage among 12-18 years old youngsters towards school activities. The findings reveal that the Internet was used by about half of the participated youngsters mainly for communication. Even though the second highest usage was on information searching, the relationship between Internet usage and school practices was insignificant. Moreover, boys are using the Internet more extensively than girls. This denotes that educated people are using Internet not only for educational but also for other purposes.

In their study, Omekwu, Eke, and Odoh (2014) indicate that most of the undergraduate students of Nigeria University, Nsukka, used the Internet to visit social networking sites for a variety of preferred occasions. Among them are to communicate with friends, watch movies, discuss on national issues, such as politics, economy, and religious matters, and fulfill academic purposes. This proves that their performance is not affected even though the students are using the for other purposes besides academic.

In many countries, youngsters (18-34 years old) are more likely to indicate that the Internet provides good influence when compared to older generation (ages 35+) (PEW Research Center, 2015). This is true, especially its influence on morality, education, and personal relationships. For example, 48% of Vietnamese, 73% of Ukrainian, and 71% of Lebanese youths pointed out that the Internet has a good influence on morality, education, and personal relationships, accordingly. This signifies that young people who are using the Internet will give positive feedbacks, particularly on the numerous benefits and advantages.

In addition, the highly educated individuals are much more likely to see the Internet as a positive force in their country. For example, a research conducted across 29 countries indicated that 70% of those participants with a secondary education or higher and 59% with lower stated that the Internet has good influence on education. Similar gaps were also found between the more and less educated individuals on the perceived influence of the Internet on all the tested aspects.

2.7.1 Internet Usage and Student Performances

The literature related to the impact of Internet usage on student's academic performance has shown mixed results. The arguments on the relationship between Internet usage and students' performance have been classified into two groups; the first supports the positive relationship between them (Siraj et al., 2015; Chang et al., 2014; Kumar & Manjunath, 2012; Ogedebe, 2012; Oskouei, 2010), whereas the second claims that the Internet usage gives negative impact on students' performance (Cerretani, Iturioz, & Garay, 2016; Wanajak, 2011; Englander, Terregrossa & Wang, 2010). However, one study indicates no significant relationship between the two variables (Ellore, Niranjana, & Brown, 2014). This shows that previous related studies provide inconsistent (Englander, Terregrossa, & Wang, 2010) and contradicting results.

Siraj et al. (2015) investigated the relationship between the impact of Internet usage on the academic performance of medical students. Their empirical study involved 234 year-4 UKM medical students of the 2011-2012 academic session. The findings show that the students who were using the Internet for more than six (6) hours during weekdays and weekends achieved higher CGPA. Similar findings were also reported by Oskouei (2010) in which a student who spent more time using the Internet

attained a higher average academic score than the others. He further disclosed that social networks users were mostly good students as compared to the weaker.

It was found that the main purpose of using the Internet was to prepare and complete course assignments, which in turn helps the students to improve their academic performance (Siraj et al., 2015; Ogedebe, 2012). Ayub, Hamid, and Nawawi (2014) revealed that Internet usage for academic purposes among students was moderate, whereby only social sciences and agriculture students have used it significantly. This trend contradicts to the general perceptions in Pakistan that associate the Internet with entertainment (Bashir, Mahmood, & Shafique, 2008).

While majority of the previous researchers studied the effect of Internet usage on students' academic performance, Chang et al. (2014) investigated how Internet self-efficacy helps students to transform motivation into learning action that will influence learning performance. Internet self-efficacy plays an important role in influencing learning performance; pre-test scores on students' perceptions of Internet self-efficacy affect their final examination marks. The study concludes that students with higher Internet self-efficacy performed better in final examinations than students with lower Internet self-efficacy. In terms of gender, male students have higher Internet self-efficacy that will lead towards better learning performance and academic grade.

On the other hand, the views that rejected the positive relationship between Internet usage and students' academic performance were raised by many scholars, such as Madhavika and Kodithuwakku (2019), Cerretani, Iturioz, and Garay (2016), Wanajak (2011), and Englander, Terregrosa, and Wang (2010). This group argued that high usage will lead to Internet addiction. This finding is consistent with the

those of the previous studies (Lin, Ko, & Wu, 2011; Wanajak, 2011). The amount of time spent on the Internet has been reported to be an influencing factor for Internet Addiction. Wanajak (2011) stressed that addictive Internet users spent approximately 29 hours per week on the Internet as compared to normal users of 16 hours. However, they did not examine the effect of Internet addiction on students' performance, which requires further research.

Similarly, the Internet usage of the 128 students in an introductory microeconomic course negatively affected their academic results (Englander, Terregrossa, & Wang, 2010). Thus, the researchers concluded that the Internet does not provide a rich source of knowledge and ideas that can foster students' academic performance and nourish other positive objectives. This opinion coincides with that of Loughheed (2002) and Young (2004) that the Internet offers many unproductive enticements that may divert students from beneficial purposes.

All the above literature indicates the positive and negative relationships between Internet usage and students' academic performance. Although most research denotes positive relationships, the results of the actual academic performance are still unclear. For example, study by Ellore, Niranjan, and Brown (2014) gave different results. The study focused on finding the influence of the Internet, Facebook, and online media usage regarding education, non-education, polychronicity, and interest on students' academic performance and face-to-face communication skills of college students. The results show no significant effect on Internet usage and students' performance. One of the reasons of having the non-significant result is that students have control over the use of the Internet.

From the above discussion, it is noted that the studies that investigated the relationship between Internet usage and students' academic performance are inconsistent results and have not proven significant accomplishment. In addition, the existing studies shared different views and focused on various areas from what the researcher have been searching for. Therefore, this study tries to overcome this gap in the literature. Table 2.4 summarizes the past research that looked into the relationship between Internet usage and students' academic performance. This table highlights the latest studies that have been conducted.

Table 2.4.

Summary of the Previous Studies that Examined the Relationship Between Internet Usage and Student's Academic Performance.

No.	Authors	Findings	Positive / Negative
1	Fernandez-Gutierrez, Gimenez, & Calero (2020).	The effect of internet on educational outcomes is non-significant for maths and reading, and positive for science.	Positive
2	Madhavika & Kodithuwakku (2019)	There is a statistically significant impact of Internet usage on academic performance of Sri Lankan Undergraduate students, which is positively correlated.	Positive
3	Siraj et al. (2015)	This study found that high Internet usage brings better academic result as students get the opportunity to enter the information world.	Positive
4	Chang et al. (2014)	Students with high Internet self-efficacy outperformed those with low Internet self-efficacy on the final examination.	Positive
5	Kumar & Manjunath (2012)	The results have shown that the use of Internet appears to have a very positive impact on the work of teachers and researchers.	Positive
6	Ogedebe (2012)	The Internet has been shown to influence the academic performance of students both at the local and international levels.	Positive
7	Oskouei (2010)	Highly Internet users mostly were good students while weak students had less usage of internet	Positive

8	Ladron de Guevara Rodríguez et al.(2022).	The use of the Internet and social networks may lead to “addiction” that may affect their academic performance.	Negative
9	Feng, Wong, Wong, & Hossain, (2019).	It also found that academic distraction plays a mediating role in the indirect effect of Internet and Facebook usage on students’ academic achievement. T	Negative
10	Xu, Wang,Peng, & Wu, (2019)	the features of Internet behaviors are significant correlated to academic performance.	Negative
11	Cerretani, Iturioz, & Garay (2016)	The study found that the younger the students, the higher the use of ICT, and the higher the usage, the poorer academic performance.	Negative
12	Wanajak (2011)	Students who reached a higher level of Internet usage are categorized under Internet Addiction.	Negative
13	Englander, Terregrossa, & Wang (2010)	The study finds a negative and statistically significant impact of Internet usage on students’ performance.	Negative
14	Ellore, Niranjana, & Brown (2014)	The study found that there is non-significant relationship between Internet usage and academic performance.	No significant relationship

2.8 Underpinning Theories

This section explains and reviews the underpinning theories that have been adopted in this study. A theory is a set of interrelated concepts, definitions, and propositions that explains or predicts events or situations by specifying relations among variables. Generally, a theory consists of two main ingredients, which are concepts and principles (Moore, 1973). In the light of the above, this study proposes that PKV model should encompass the three characteristics of theories found in the past related literatures. These past related literatures worked on Process Visualization Theory (Overby, 2008), Cognitive Load Theory (Sweller, 1988) and Decision Making Theory (Simon, 1979). In the next paragraphs, a brief description about each of the theories are given.

2.8.1 Process Visualization Theory

The model of this study is introduced by using the Process Visualization (PV) theory. The theory, formulated by Overby (2008, 2010), describes on how cognition can be achieved through visualization. This theory seeks to explain and predict whether processes that have been traditionally conducted in physical environments can be migrated to virtual, particularly those related to information technology. The theory also describes the factors (sensory, relationship, synchronism, identification, and control requirements) and information technology characteristics (representation, reach, and monitoring capability) that influence the suitability of a process, which will be conducted virtually. Figure 2.2 illustrates the Process Visualization Theory introduced by Overby (2008).

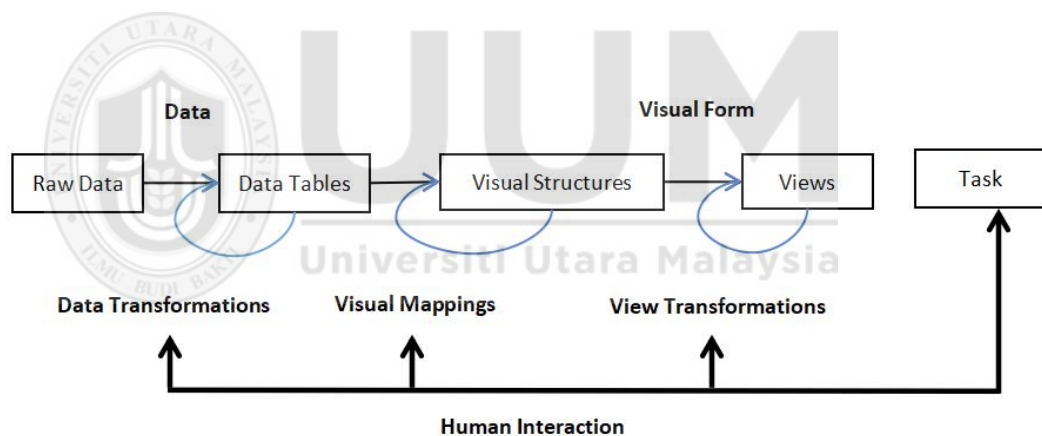


Figure 2.2. Process Visualization Theory (Overby, 2008)

The PV theory has been used in several research settings, such as the automotive wholesale market (Overby 2008) and telecommunication sector (Czarnecki, Korner, & Piclum, 2010), and cross-channel instant messaging (Li & Gupta, 2009). Since its development in 2008, the Process Virtualization theory has been applied in numerous studies. The theory has turned into a hot topic, especially during the prevalence of IT application. Among the most influential studies that highlighted the significant contributions of the Process Virtualization Theory are those by Hong and Li (2009);

and Thomas, Costa and Oliveira (2015) to. Hong and Li (2009) emphasized that most organizations were moving towards virtualization, in which more and more business workflows are operating through various ICT means. However, some processes were more amenable to virtualization. The three variables that should be considered are workflow virtualization, media richness, and user control.

As for Thomas, Costa, and Oliveira, they tried to assess whether IT-enabled process virtualization capabilities impact organizational Green IT initiatives by proposing a conceptual model that combined the Process Visualization Theory (PVT) and Technology-Organization Environment (TOE). PVT provides the technological basis of process virtualization. Their research contribution relates to the discovery of new knowledge to the emergent area of IS research by providing insights on the impact of the virtualization process on Green IT initiatives. Therefore, the PVT is considered compatible theories that will use in this study because it will lead to the conversion from manual decision making process to the support system that help decision making make decision by embedding IT injections.

2.8.2 Cognitive Load Theory

Cognitive Load Theory (CLT) was developed by John Sweller on 1988. It is one of the prominent theories in instructional domains based on the understanding of human cognitive architecture (Sweller et al., 2011). CLT has been widely used in various domains, such as education, multimedia, aging and learning, affective computing, and programming tutorials. Cognitive load relates to the amount of information that working memory can hold at one time. According to Sweller, since working memory has limited capacity, instructional methods should avoid overloading it with additional activities that do not directly contribute to learning. This theory builds

upon the widely accepted model of human information processing, shown in Figure 2.3, as adapted by Atkinson and Shiffrin (1968). It describes the process as having three main parts of memory; sensory, working, and long-term.

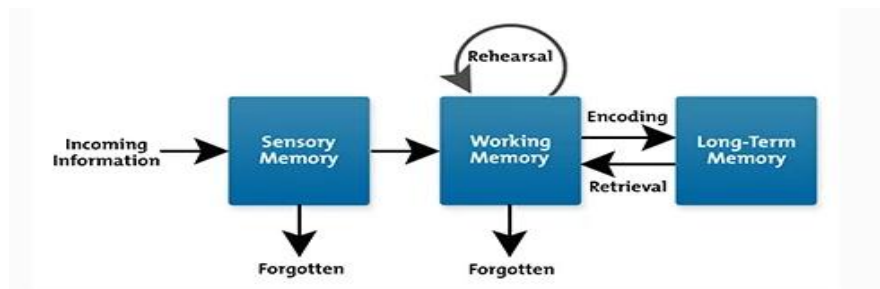


Figure 2.3. Cognitive Load Theory (CLT) (Sweller, 1988)

Few studies, as observed by Liu and Stasko (2010), have examined the interplay between the external representation of data using visualizations and its corresponding internal representation of mental models within the human's cognitive faculties. CLT adequately describes this phenomenon. It is one of the problem-solving theories that suggested the interaction between the problem-solving tasks and results presentation (visualization) in amplification of cognition (Teets Tegarden & Russell, 2010). Most importantly, CLT suggests that mental representation of a problem can only be realized when the representation fits the problem-solving task.

Speed and accuracy of the problem solving process can be achieved by the compatibility of users' interaction and subsequent internalization of the data displayed through the infographics. CLT has also been expanded extensively to decision-support from its tasks classification-symbolic, spatial, and exploration to reduce users' cognitive load (Teets Tegarden & Russell, 2010). By using the concept from CLT, it will be as a basic theory that will applied in this study to expand the

decision support by using visualization to reduce the mental efforts of decision maker.

2.8.2.1 Cognitive Load Measurement

The measurement technique for cognitive load becomes important as it indicates the amount of mental efforts imposed on a person to complete a particular task by determining the level of cognitive load and providing insights to ensure better performance (Hussain, Calvo, & Chen, 2014). Three widely accepted techniques for measuring cognitive load are; 1) subjective-measurement (self-rating), 2) task-performance measurement, and 3) behavioural and physiological measurements.

The first subjective-measurement or self-rating measurement has been implemented to measure the mental effort experienced by participants after completing a task (Martin, 2014). The second technique, task-performance measurement, developed by Paas (1992), consists of a nine-point scale construct ranges from (1) as very low to (9) as very high (Van Gog, Kirschner, Kester, & Paas, 2012). This measurement has been used in many psychological studies to capture the level of load imposed by a learning task (Sweller et al., 2011). As an alternative to this, the seven-points scale was developed to evaluate cognitive load by preserving the original formal scaling method (Kalyuga, 2012). On the other hand, the task-performance measurement was also used as an objective technique to assess the level of cognitive load focuses on either the single or dual-task performance (Brunken, Steinbacher, Plass, & Leutner, 2002). This method has been applied in various studies to measure whether human performance will be increased with lesser load or vice versa (Endres, 2012). This approach is more objective than the self-rating due to its less disruptive nature.

The third technique refers to the behaviour and psychological measurements. This method is intrusive due to the implementation of some bio-sensor devices, such as electrocardiography instruments to measure the electrical activity of the heart of a period time (Durantin, Gagnon, Tremblay, & Dehais, 2014) and an eye tracker device to measure the point of gaze or motion of an eye relative to the head (Palinko, Kun, Shyrokov, & Heeman, 2010). The usage of these devices may cause discomfort for some participants due to its intrusiveness. Other devices that can be used to capture cognitive load are speech recognizer (Huttunen, Keranen, Vayrynen, Paakkonen, & Leino, 2011), pen input (Ruiz, Taib, Shi, Choi, & Chen, 2007), and electroencephalography (EEG signals) to capture electrical activity of the brain (Knoll et al., 2011).

2.8.3 Decision Making Theory

The main purpose of the Decision Support System (DSS) is to support decision-making in an organization, assuming that the way in which the process actually takes place is fully understood. There are various views and theories on decision-making as provided by Keen and Scott Morton (1978), Simon (1979), Huber (1981), and Das and Teng (1999). These views and theories, presented in Table 2.5, can be utilized to support this research.

Table 2.5.
Decision Making Models

Model Name	Author	Description
1) The Rational model for decision-making	Craik & Leibovich, 1976	The process of rational decision-making comprises a number of steps: 1) Intelligence: finding occasions for making a decision 2) Design: inventing, developing, and analysing possible courses of action 3) Review: assessing past choices.
2) The multiple perspectives approach	Churchman, 1971	This approach classifies perspectives as either being technical, organizational, or individual in nature.
3) The organizational procedures view	Cohen, March & Olsen, 1972	The organizational steps view required to grasp decisions as the output of standard operating procedures mentioned by organizational sub units.
4) The individual differences perspective	Keen & Morton, 1978	This model focuses on the intention to the problem-solving behaviour of the individual manager, as influenced by the managers' decision-making manner, background and personality. It tries to demonstrate how managers may use various means or outcomes because of differing personalities.

As mentioned in Table 2.5, the multiple view classifies perspectives as either being technical, organizational, or individual in nature. Different analysts or modelling projects will come up with diverse technical views. However, in this study, the perspectives from Simon (1979) are chosen based on the process that introduced by Simon relating the rational decision-making and provides a number of steps in the Decision-Making Theory (DMT), which include 1) intelligence, involving finding the occasions for making a decision; 2) design, involving finding possible courses of

action; 3) choice, involving the selection of a particular course of action from those available; and 4) review, assessing past choices. This step is a perfect rationality, methods of decision analysis, is used to attach numerical values or utilities to each of the alternatives during the “choice” phase. The alternative with the highest utility (or maximum subjective expected utility) will be selected. When using the rational model in an organization, it is assumed that managers are aware with all the possible alternatives and consequences of implementing each alternative. Managers must have a well organised set of preferences for such consequences and the computational ability to compare consequences and to determine the most preferred.

2.8.4 Implications of the Theoretical Background of the Study

The implication of the theoretical explanation and deductions is both the design and evaluation of the PKV model and prototype is delivered in this study. This approach of theoretical application is supported by some of the past related studies. Each of the theories discussed in this study characterized a particular support based on the three basis in which the PKV must be designed for. The process of designing is to ensure that the principles of the theories are reflected in the design features of the PKV. The theoretical guide, as presented in Table 2.6, highlights the design features that correspond to the PKV techniques and attending theories.

Table 2.6.
Theories that Support PKV model

Theory	Category Support	of	Design Features	References
Process Visualization Theory (PVT)	Perceptual	Data relationship, focused	object Domain	Overby (2008) Overby & Konsynski (2010)

Cognitive Theory (CLT)	Load	Cognitive	Interactive media, communicative graphics.	Sweller (1988)
Decision Theory (DMT)	Making	Decision Making	Users' control	Simon (1979)

From the presented review, this study attempts to identify a theoretical contribution by proposing a theory-based design to ensure that the PKV model can support perception, cognition, and decision-making. The design features that will drive these supports are respectively listed.

2.9 Summary of the Chapter

This chapter presents a review of literature related to the areas of study, which is Knowledge Visualization, Prescriptive Analytics, Visual Analytics, and Overview of Institution of Higher Learning. Moreover, the underpinning theories are introduced in this chapter and discussed in detail. It includes detailed discussion on related theories of visualization, cognitive load, and decision-making theories and its implication towards this study. In the context of this study, the research gaps have been identified and addressed, in order to provide an assistance to develop PKV model. The next chapter introduces the research methodology to develop the PKV conceptual model for this study.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the methods and techniques adopted in this research are described. It discusses the research processes in holistic and presents all the methods used in achieving the stated objectives. The chapter explains research method, research design in details, research population and sampling as well as research instruments.

3.2 Research Method

The research method is generally accepted as the procedures of answering the research questions (Cresswell, 2009). The design research methodology conceptualized by Hevner et al. (2004) with its phase-to-phase approach is adopted for the accomplishment of this study's objectives. In the methodology, the primary focus is on delivering artifacts such as models, methods, or prototypes. Hence, it is mostly adopted by researchers in the information system design.

Most researches in the IS discipline is characterized by two paradigms: design science and behavioral science. Design-science is a research paradigm that extends the boundaries of human and organizational capabilities by creating new and innovative artifacts. The behavioral science paradigm- seeks to develop and justify theories (i.e., principles and laws) that explain or predict organizational and human phenomena surrounding the analysis, design, implementation, management, and use of information systems (Hevner, March, Park, & Ram, 2004).

Having identified the business needs, research is conducted in two complementary phases - design science (develops and builds) and behavioral science (justifies and

evaluate). During the design science phase, the researcher addresses the research through the building of artifacts designed to meet the identified business needs. The applicability of the designed artifacts to the business needs is then evaluated during the behavioral science phase. The knowledge base provides foundations (theories, frameworks, instruments, constructs, models, methods, and instantiations) and methodologies (data analysis techniques, formalisms, measures, and validation criteria) that have resulted from prior research studies. Foundations are used during the design phase, while methodologies are used for evaluation during the behavioral science phase. Based on this framework, the contributions of design science and behavioral science are assessed by (i) applying to the business needs in an appropriate environment, and (ii) the value added to further research and practice as the result of adding to the contents of the knowledge base (Hevner et al., 2004).

The research design for this study is influenced by the IS framework proposed by Hevner et al, (2004). As it is based on both behavioral science and design science paradigms, the research design for this study utilizes the design science paradigm as a research approach to innovate new artifacts. In the current study, there are four phases of major activities involved in Figure 3.1 namely (a) Problem Definition, (b) Suggestion (c) Development, (d) Evaluation and, (e) Analysis, Findings and Conclusion. The research process illustrates the phases, process, activities involved and outcome for each phase. In the context of this study, the overall research methodology steps and its activities are illustrated in Figure 3.1.

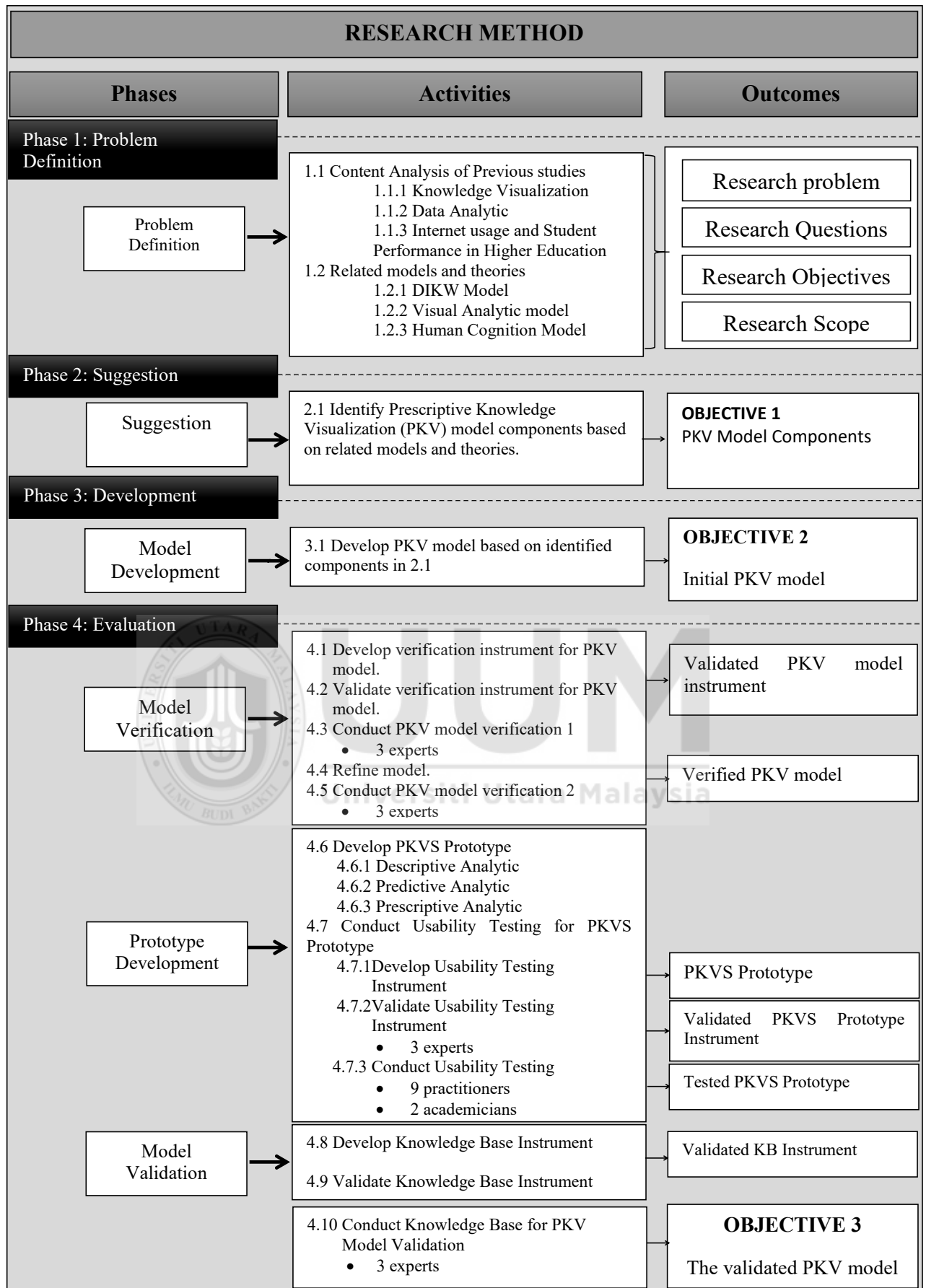


Figure 3.1. Research Design

3.3 Research Design

The design research was chosen as it represents an appropriate research methodology that aligns with the main objective of this study; developing a PKV conceptual model for decision maker. The design research paradigm is suitable for the achievement of a design model/framework and a popular methodology in fields of Human Computer Interaction (HCI) (Rosson & Carroll, 2002; Druin et al., 2002), Information System (Vaishnavi, Kuechler, 2007; Purao, 2002), Education Research (Barab & Squire, 2004), and Instructional Design (Regeluth et al., 2009).

In HCI, several researches have employed design research. Carroll (2000) declare that a design research should be of two goals. First, to understand the world through design requirements gathering process. Second, to improve the world by creating tools that will solve human problems. As for (Hevner et al., 2004), design research in information system focuses on problem-solving purposes with an attempt to create innovations that define ideas, technical abilities, and capacities. Moreover, it produces abstraction and representation models, algorithms and practices methods, symbols and vocabularies, as well as prototyping instantiations (Hevner et al., 2004; Vaishnavi & Kuechler, 2007). This summarizes the descriptions of design research and the basis of its suitability to be applied in this study.

3.3.1 Justifications for Using Design Research

Design research is appropriate for this study due to the availability of required phases and expected deliverables. Further justifications are as follow:

The design research attends to the problem of artefact design. Specifically, in this study, one of the deliverables is a conceptual design model. Therefore, model

development fulfill the purpose of adopting design research (Hevner et al., 2004; Teegavarapu & Summers, 2008; Frankel & Racine, 2010). Most importantly, the domain of this study (Information system research) suits design research (Hevner et al., 2004).

The design research guidelines, as outlined by Hevner et al. (2004), Teegavarapu and Summers (2007), and Frankel and Racine (2010), are relevant and practical to be utilized in this study.

In short, the use of design research fits the development of the PKV conceptual model to support decision-making related to internet usage and students' academic performance.

3.4 Phase 1: Problem Definition

In the first phase, the literature review and preliminary study were conducted to define and understand the identified problem. The content analysis technique (Babbie, 2010; Creswell, 2009) was employed to identify the research gap and related key issues. The outcome of this phase was the formulation of the research problem, questions, and objectives as discussed in Sections 1.2, 1.3, and 1.4, respectively.

Content analysis is a process of extracting sufficient knowledge about a proposed study. It was performed to seek information and facts from various sources, such as books and articles. Others may include text, audio, and components, which are stored in different databases (Rogers, Sharp, & Preece, 2023). In this study, the main aim of the content analysis is to gather relevant concepts and theories in proposing a PKV model that supports the decision-making process in IHL.

A theoretical framework is another criteria that can be used to determine research gaps (Norshuhada & Shahizan, 2010). As for this study, previous literature related to visualization, analytic, Internet usage and student performance in IHL was reviewed to find the issue and gap. The data acquired from secondary sources was analyzed to see the pattern and to define the problem. The base theory was also reviewed to present a theoretical guide to the design and evaluation of the PKV model to ensure that the delivered prototype supports the cognition and reasoning for the decision-making process.

3.5 Phase 2: Suggestion

The main purpose of this activity is to determine the appropriate elements of proposed model. At this stage, all components gathered that are related to knowledge visualization and prescriptive analytics were compiled and integrated into PKV design model. At this second phase includes two activities; suggestions for model development and combining three models, DIKW, Visual Analytic, and Human Cognition, into one. The outcomes from the first phase were utilized to accomplish the first objective. The suggested analytic techniques, based on the results and Internet usage patterns obtained from the content analysis procedure were embedded into the KV model. The mapping of these three models was suitable to develop the PKV model. The details about the suggestion phase is illustrated in Figure 3.2.

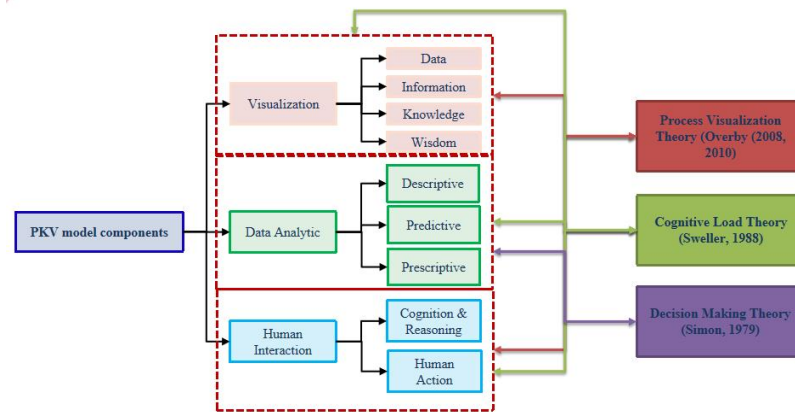


Figure 3.2. The Design Mapping in Suggestion Phase

The main purpose of the suggestion phase as illustrated in Figure 3.2 was to determine the appropriate elements of the proposed model. Many existing KV models, approaches, and methods as well as many real-world solutions have been reviewed in order to identify required phases, components, and model's functions for this model. At this stage, all components related to Knowledge Visualization and Prescriptive analytics were compiled and integrated into the PKV design model. In addition, the DIKW (Data-Information-Knowledge-Wisdom) model, also known as hierarchy, was chosen based on its ability to process and transform data into information, knowledge, and wisdom.

In data analytics, a data scientist will not obtain required results by simply making a guess based on intuitive. The actual activities involved the gathering of data, synthetization of information, acquiring and applying knowledge as well as guidance from wisdom. The activities were based on the visual analytic and Human Cognition concepts facilitated by interactive visual interfaces. Both concepts are popular models for classifying human's understanding in the perceptual and cognitive space. The models also provide a graphical representation of how knowledge can be transferred that requires human and computer analysis.

3.6 Phase 3: Development

The construction of the PKV model for supporting the decision-making for Institutions of Higher Learning (IHL) is one of the specific objectives in this study. This model acts as a general framework through the presentation of various functionalities (Jones & Malik, 1992; Szeliski, 2022). This design model contains components derived from the existing visualization models, approaches, and methods. A number of those existing models, approaches, and methods as well as other real-world KV solutions have been reviewed to identify the required phases, components, and functions for the development. The model includes objects and relations to indicate a system's organization and operation (Hollingworth, & Henderson, 2002; Rogers, Sharp, & Preece, 2023). The proposed model development involved three steps: i) building the goal structure, ii) combining the analytics approach, and iii) delivering the new model to respective decision-makers. Then the model was validated in an iterative manner using expert review and usability testing. The following section highlights on the evaluation process.

3.6.1 PKV Model Development

This section describes the proposed model's development process. After conducting a content analysis and review of related literature, the phases and components of the proposed model are formulated. All these components and phases are combined to build the first version of the proposed model. Therefore, the PKV proposed model consist of two core phases:

- i. PKV Requirements Gathering.
- ii. PKV Model Development.

Each of these phases of the PKV model was mentioned above are contain a set of sub-phases or components. The detail of each phase is described in the next section.

3.6.1.1 PKV Requirements Gathering

Requirements gathering is an important and necessary component of any model development and considered a cornerstone to the success of any project. The main objective of this activity is to identify the elements, components, phases, and data flow that require to develop PKV model that suite to the domain of this study. The scope of this study is to enhance of the decision-making process to solve the issue of the student performance based on their internet activities. The main activities were reviewing the literatures by comparing existing models. Various theories and models were reviewed to develop the conceptual model for this study. Table 3.1 lists the core components and main contribution of existing models that were used when developing the proposed model.

Table 3.1.
Core Components and Main Contribution of Existing Model

Author's	Models' Name	The Components	The Models Contribution
Ackoff (1989)	DIKW Model	Data, Information, Knowledge, Wisdom, Meaning and Value	To classify human understanding regarding perceptual cognitive space.
Scha et al.(2014)	Knowledge Generation Model for Visual Analytics	Data, Visualization, Model, Knowledge	To generate knowledge to solve cognitive issue through visualization

Green et al.(2009)	Human Cognition Model	Discovery through Knowledge Creation, Search by Patterin, Computer and To revolutionize the Human at Initial State, cognition in the Computer Aided Discovery visualization design. and Generation and Analysis of Hypotheses.

From the table above, it can be seen visualization is an important component to derive knowledge from the information. However, this study is contributed to transform the knowledge that has been developed and convert knowledge into action and the existing model is not achieved that objectives. Hence, other components need to be added to cater the cognitive issue and generate understanding better than the knowledge has been generate will turn into action which known as wisdom. In consequence, this activity has identified the key elements of PKV model such as phases, components, activities, and flows for the development of PKV model. The findings were then integrated in the proposed model. In the next will discuss the next step after requirements gathering.

3.6.1.2 PKV Model Development

The proposed model was based on the results of the previous phases. At this stage, the interconnection between the related model that support knowledge visualization and data analytic. The conceptual model is also theoretically supported based on the theoretical guide to designing prescriptive knowledge visualization model. This study also presented structural and process models as supporting components to the conceptual PKV model. The model development phase for PKV model is shown in

the Figure 3.3 and the proposed PKV model is presented in Chapter 4 of this thesis.

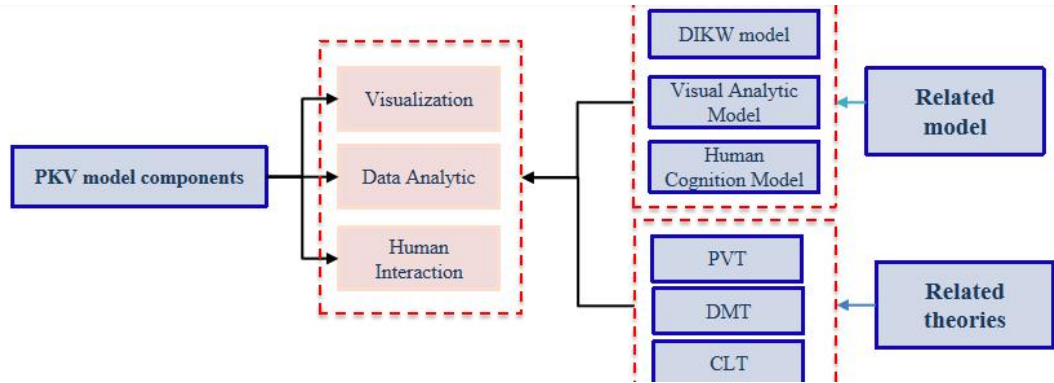


Figure 3.3. Model Development Phase

3.6.2 Initial Model Verification

In general, initial model verification attempts will concentrate on the output of the model, and only if that verification suggests a problem will more detailed validation be undertaken. At this stage, the conceptual model was firstly verified using expert review. The experts, as referred to in this study, are academicians who have prior experience in knowledge visualization and data analytic.

According to Nielsen (1997), a number of three (3) to five (5) experts are sufficient for expert review. This study uses five (3) experts drawn from academics. The profile of the experts is presented in Appendix. At this stage, the model verification are conducted before the prototype development based on the model. The procedure of model verification include, (a) designing the review instrument based on the chosen metrics for the evaluation (detail in section 3.10), (b) conducting the review, and (c) analysing the results (d) model refinement, and (e) model verification stage 2. The detail of the model verification results is discussed in Chapter 6.

3.7 Phase 4: Evaluation

In verifying of the proposed PKV model as well as to revise and modify it, the evaluating process was conducted. This study employed the experimental method for

the evaluation, comprising 1) expert review, 2) Usability Testing from the PKVS prototype and 3) Knowledge Base from the expert as suggested by Rogers et al. (2011), and Shneiderman and Plaisant (1996). Among the usable methods in evaluating and validating research outcomes are experimentation, demonstration, metric usage, simulation, benchmarking, logical reasoning, and mathematical proofs (Vaishnavi & Kuechler, 2007). These methods have different strengths and appropriateness. However, the selection of an evaluation method must be based on the expected research outcome. Three main goals derived from the evaluation are; (i) to assess the extent and accessibility of the system 's functionality, (ii) to assess user's experience of the interaction, and (iii) to identify any specific problems with the system (Ellis & Dix, 2006; Dix, 2002). In the context of this study, the experts in expert review method are not the same the participants with expert review for Knowledge Base experts as well as usability testing expert to obtain the reliable result in the model verification, model refinement and model validation. Furthermore, this evaluation process is an extensive and iterative process, and is discussed in the next sections.

3.7.1 Expert Review

As mentioned in previous section, one of the model validation methods that has been used in this study is expert review. The PKV model verification was conducted by expert review method after the instrument was successfully validated. The expert review is recognized as a way of improving the quality of the developed conceptual model (Wieggers, 2002). According to Morgan (1996), the expert review is one of the accepted techniques used to verify the appropriateness of the proposed model. The expert review was done by considering the appropriateness of the proposed model using measurement and dimensions adapted from Syamsul (2011) seigneur et al.

(2000), Hecksel (2004), Kerzner (2006) and successfully verified by the five (5) experts in the Research Instruments section (see section 3.10). Hence, this study uses the expert review technique to verify the PKV model. In this study, two steps of model verification were conducted which are 1) Model Verification 1 and after verified by expert review and do model refinement then 2) Model Verification 2 take places. Both these two model verification stage 1 and stage 2 conducted with different experts. Three (3) experts are chosen based on areas of specialities align with this study for each model verification stage. The demographics profiles of experts that participated in the model verification 1 review session are presented in Table 3.2.

Table 3.2.
Demographic Profiles of Experts in Model Verification

No.	Qualifications	Gender	Expertise	Year of Experience
Expert A	PhD in Computer Science	Male	Information Analytics System,	30 years
Expert B	PhD in Software Engineering	Male	Data Warehousing, Intelligent Database, Data Structures	27 years
Expert C	PhD in Computer Science	Female	Machine Learning, Data Mining, Predictive Analytics	19 years

From the table above, three experts from academicians who have more than 15 years' experiences are involved in model verification 1. The experts, as referred to in this

study are academicians who are experts in analytics and have prior experience in developing visualization tools.

After model refinement, the model verification stage 2 is conducted with another three (3) experts. 3 experts are adequate to verify the proposed PKV model for the stage 2. The 3-experts come from computer engineering and computer science who has more than 10 years' experience in this field. The demographics profiles of experts that participated in the model review session are presented in Table 3.3.

Table 3.3.
Demographic Profiles of Experts in Model Validation

Experts	Qualifications	Gender	Expertise	Year of Experience(s)
Expert D	PhD in Computer Science	Female	Computational linguistics, artificial intelligence, machine learning and content-based information retrieval.	11 years
Expert E	PhD in Computer Science	Male	Software Engineering and Information System Development.	14 years
Expert F	PhD in Software Engineering	Male	software engineering, empirical software engineering, mining software repository, social network analysis, socio-technical congruence, computer supportive collaborative work, and software process	14 years

3.7.2 Usability Testing

The usability testing was performed through the experts' interaction with the prototype using their heuristic experience (Tory & Moller, 2005). In achieving reliable findings, two usability experts representing two distinct job positions (IT officer and IHL decision-maker) were selected to validate the knowledge base. Finally, it is noteworthy that the PKV functionality intersects between visualization and decision support.

3.7.3 Knowledge Base

In this section, the approach for decision maker to make decision based on the IUB in IHL from the knowledge base is presented using an example to demonstrate the feasibility and practicability of the proposed model. After evaluating the proposed PKVS prototype, different recommendations or suggestions from the PKVS prototype to the decision maker to solve the issue of IUB and student performance is stored in a knowledge base for further use. This knowledge base are tested with the expert review consists of IHL decision maker in term of 4 dimensions to validate the PKV model. Five dimensions values that are stored in the knowledge base are specified for this validation criterion that will mention in details section 3.10.3.

3.8 Phase 5: Analysis, Findings and Conclusion

The data analysis resumed after the completion of the initial four phases. The choice of analysis method usually depends on the nature of data collected (qualitative and quantitative) and objective of the evaluation study. In the current study, the data analysis process was conducted by using the three phases of quantitative method. The quantitative method was used in this study to achieve the second and third

objectives. Hence, the analysis followed the quantitative data analysis method. The two most commonly use quantitative data analysis methods are descriptive and predictive analyses. However, prescriptive analysis was introduced to achieve the main goal of this study.

3.8.1 Descriptive Analysis

Typically, descriptive statistics, also known as descriptive analysis, refers to the first level of analysis. The analysis helps to summarize and model the data. A few commonly used descriptive statistics are mean, median, mode, percentage, frequency, and range. Descriptive statistics provide absolute numbers. However, they do not explain the rationale or reasoning behind those numbers. In this study, the frequency of Internet usage among students as well as the percentage of Internet category were analyzed to the differences. Students' CGPA was also analyzed by using descriptive analysis to group students' performance and map with students' Internet activity.

3.8.2 Predictive Analysis

Predictive analysis is used to generalize results and make predictions about a larger population. These are complex analyses that show the relationships between several different variables, rather than describing a single variable. They are used when the data needs to go beyond absolute values and understand the relations between variables.

Based on the second objectives, this study conducted predictive analysis to determine the correlational between Internet usage and students' academic performance. The purpose of using correlation is to describe the relationship between two variables. If a correlation were found, it means that there is a relationship among the variables. These analyses were conducted using the IBM SPSS Statistics (SPSS) for data entry,

screening, and preparation to identify missing and non-compliance data, followed by the main analysis.

3.8.3 Prescriptive Analysis

The aim of this study is to prescribe the solution and recommendation to decision-maker based on Internet usage activities to improve students' performance. Therefore, to achieve the goal, the prescriptive analysis was conducted after the predictive analysis. This technique allows the system to finalize the possible solution based on students' Internet usage patterns and impact on their performance. By applying the regression technique, the data was scrutinized to generate the best solution with weighted risk. Finally, recommendations in the form of weighted options will be provided to the users to ease decision-making.

3.9 Research Sampling

Population refers to the entire elements or group of people, events, or things of interest that a researcher wishes to investigate (Sekaran, 2003). The samples used in this study constitute a) IHL students b) academic with prior knowledge, c) usability experts, and d) IHL policy makers.

The population of this study comprises students from Institutions of Higher Learning in Malaysia. However, due to the time limitation and data confidentiality, it is impractical to gather the data from all Institutions in Malaysia. Therefore, a sample is sufficient as long as it is representative of the whole population and a conclusion can be generalized on all members of the population (Sekaran, 2003; Gay & Diehl, 1996).

In Malaysia there are 20 public universities and 24 private universities. However, the researcher only chose one university as a case study, which is Universiti Utara Malaysia (UUM) as the target population. The selection was based on the following

justifications. UUM, located in a Northern region state of Peninsula Malaysia, has a sufficient number of national and international students. Thus, it is relevant to use it as the sample for this study for identifying the effectiveness of Internet usage among students. Next subsection will explain the sampling techniques that apply in this study.

3.9.1 Sampling Techniques

According to Kumar and Vijayalakshmi (2011), sampling refers to “the process of choosing a portion from a larger group to serve as the foundation to estimate the prevalence of unknown fragment of related information, scenario, or findings”. Creswell (2009) defined sample as a subgroup of a target population that a researcher plans to study for generalizing. Failure of choosing a proper sampling technique will lead to difficulties in collecting required data. Sampling methods are categorized into probability and non-probability sampling (Rea & Parker, 2014). Probability sampling method ensures an equal chance of being selected for each member of the population, while non-probability allows a researcher to choose appropriate respondents according to the nature of the problem being studied. Thus, this study used the non-probability sampling method because the secondary data that need to be collected relate to the top 50 highest students who frequently used the Internet. Table 3.4 summarizes the sampling design of the current study and the sampling frame and size will highlight in the next subsection.

Table 3.4.
Sampling Design

Concept / Terminology	The Current Study
The Theoretical Population (To whom the current study aims to generalize the findings)	Students from public university in Malaysia

The study population	Public university in Northern region
Sampling Frame	Universiti Utara Malaysia (UUM)
The Sample	List of undergraduate students from UUM

3.9.2 Sampling Frame and Size

Sampling frame is a listing of the elements in the research population (Sekaran, 2003). Since the population of the study is the Institution of Higher Learning in Malaysia, the sample frame refers to the list of 20 public universities in Malaysia. In the context of the current study, the researcher has chosen Universiti Utara Malaysia as a sample frame.

The unit of analysis and sample size in this study was based on the number of Internet users among UUM students obtained from UUMIT. From the discussion with the person in charge, out of the thousands UUM students who were using Wi-Fi, only the top 50 highest usage can be detected for each month. Therefore, in one semester, which is equivalent to six months, the researcher was capable to collect data from 300 students. In the context of this study, the target UUM students are from undergraduate students and data about internet usage activities are collected. Therefore, the list of the undergraduate students' who is the top 50 highest using internet every month will be used and all the demographic details about the students are listed.

3.10 Experts

There are three evaluation strategies that involve experts: expert review, usability testing, and knowledge base. The instruments for all the evaluation strategies have been developed and validated by the domain experts. Nielsen (1994) supported the

choice of three to five experts for evaluation strategies. All the experts have experience in both visualization HCI and analytic techniques.

There were five (5) experts who were involved in the validation of the instruments development phase. These experts are from academicians in IS and IT from UUM and UiTM to validate the model instruments. Another three (3) experts were chosen from different universities to validate the PKVS usability testing instrument. All the experts have more than 15 years in IT domain.

The expert review was divided into two (2) verification phases which are, 1) Model Verification 1, and 2) Model Verification 2. Three (3) experts were involved in model verification 1 and three (3) experts were involved in model verification 2. The experts are the academicians who have prior experience in analytic and visualization areas.

The heuristics evaluation involved heuristics of the PKVS prototype based on the PKV model that has been conducted through usability testing. During the usability test, 11 experts consist of 9 practitioners with IT backgrounds and 2 decision makers were participated. The decision maker is the top-level managements in one faculty or in the institutions.

Lastly; the model validation involved the IHL decision makers from higher institutions to validate the model. The IHL decision makers from different public universities are used for the validation of the domain explicit knowledge. They are members of the management at the university's school, college and senate level. They are required to validate model based on the knowledge-based produce from the IUB and student performance analysis.

3.11 Research Instruments

The instruments designed for this study were:

- 1) Expert Review
- 2) Usability Testing Through Heuristic Evaluation
- 3) Expert Review Validation Through Knowledge Base Evaluation

3.11.1 Expert Review Instrument

Expert review was employed for the verifying the design of the conceptual model. The expert review instrument for this study was adapted from Syamsul (2011). The instrument was developed by adapting the design models and methodologies proposed in general software development and multimedia studies (Hecksel, 2004; Kerzner, 2006; Bonner, 2008; Shneiderman & Plaisant, 2010). The instrument's validity and reliability done by Syamsul (2011) were reported to be satisfactory. These eight dimensions are adapted based on the most appropriate to describe the dimensions to measure the cognitive and reasoning elements to achieve the research objectives of this study. All the dimensions to verify the proposed PKV conceptual model are related with the cognitive and reasoning mechanism.

The dimensions to verify the proposed design of the PKV conceptual model were complexity, visibility, flexibility, clarity, manageability, practicality and effectiveness. The expert review instrument was used by academics with prior knowledge in data visualization to verify the proposed conceptual model. Table 3.5 presents the description and source of reference of the dimensions as presented by Syamsul (2011) and adopted in this study.

Table 3.5.

Description of the evaluation dimensions of the proposed PKV conceptual design model

Dimensions	Description	Sources
Complexity	Simple to understand and use	Bonner (2008),
	Clearly understandable	Shneiderman and Plaisant (2010)
Visibility	The components and process is visible to the PKV designers and developers. They can judge the completeness and relevance of the PKV model development.	Hecksel (2004); Kerzner (2006)
Flexibility	Provides flexible development phases with negligible rigor.	Hecksel (2004) ; Bonner (2008)
Clarity	The procedure and guide on developing the PKV model are easy to follow as it includes various phases with specific steps and activities.	Hecksel (2004) ; Shneiderman and Plaisant (2010)
Manageability	The processes and activities in the model are manageable and controllable, which provides a good guide for project management.	Hecksel (2004) ; Rogers et al. (2010)

Practicality	Practical for future used	Shndeiderman and Plaisant (2010)
Effectiveness	The enhancement in productivity, effectiveness, and quality of the PKV development	Hecksel (2004) ; Rogers et al. (2011)

3.11.1.1 Develop Instrument for PKV Model

The objective of this stage is to develop the verification instrument for PKV model. The main instrument used for this review is a questionnaire which adapted from previous studies Syamsul (2011) which was developed by adapting the design models and methodologies proposed in visualization and software development studies of Hecksel (2004), Kerzner (2006), Bonner (2008), Rogers et al. (2010) and Shneiderman and Plaisant (2010).

In this questionnaire is contains seven questions asking about: (1) complexity, (2) visibility, (3) flexibility, (4) clarity, (5) manageability, (6) practicality and (7) effectiveness. Along with that, few demographic questions were also asked like age, gender, highest level of education and how many years of experience. The respondents are asked to rate each item on a Likert-scale type which are scaled by values from 1 to 7. Scale 1 to 3 for least important questions, scale 4 equals to neutral and scale 5 up to 7 equals to more important questions. Table 3.6 summarized all the items from each dimensions.

Table 3.6.
The Items for Each Dimensions.

Dimensions	Definition	Question

1) Complexity	Complexity is the degree to which a model is perceived as being difficult to use. The more complex of the model, the more difficult to use. Learning about the model should be easy, clear and understandable.	1a) The proposed model is clear and understandable. 1b) Using the proposed model does not require a lot of mental effort. 1c) The proposed model is not cumbersome to use. 1d) Using the proposed model does not take too much time from normal duties. 1e) The proposed model is simple and can be implemented easily.
2) Visibility	This visibility degree is the measurement instrument to which components and process of this model is visible to the PKV decision makers. They can judge the completeness and relevance of the PKV model development before making decision.	2a) The proposed model makes clear and visible to decision maker to make decision. 2b) The proposed model allows me to determine the completeness of the process before decision making. 2c) The phases in the proposed model are easily followed. 2d) The proposed model allows me to intelligently digest and make relevance decision making. 3a) The proposed model is adaptive and responsive to changing in user needs.
3) Flexibility	The degree of the model adaptive and responsive to users' needs then flexible for future use.	3b) The proposed model is flexible with minimal planning. 3c) All the concepts and components included are strictly necessary.
4) Clarity	The model phases and steps are easily follow. It gives a guide on the model phases.	4a) The phases in the proposed model are easily followed. 4b) The proposed model as a whole is workable. 4c) Steps or activities included are easy to apply.
5) Manageability	The process and activities in the model are manageable and controllable.	5a) The proposed model to be capable of being managed or controlled. 5b) The proposed model allows self-monitoring to be followed. 5c) The proposed model is consistent and easy to manage. 5d) The proposed model is organized and well-structured.

6) Practicality	The model is practical for future used.	6a) The proposed model is practical to be implemented in the real world. 6b) The proposed model produces results that can be used for future improvement. 7a) Using the proposed model increases my job performance and productivity. 7b) Using the proposed model enhances the quality of my work.
7) Effectiveness	The degree that PKV model enhance productivity and quality of users.	7c) Using the proposed model makes it easier to do my job. 7d) The advantages of using the proposed model outweigh the advantages. 7e) Using the proposed model produces the better result for which is intended for decision making.

From the Table 3.6, total 26 items Q-U instrument from 7 dimensions is finalized for validation purposes before send to the respondents. Next section will explain the instrument validation.

3.11.1.2 Validate Verification Instrument for PKV Model

For validating the instrument of PKV model, a content validity was conducted. Content validity refers to the degree of the items in the instrument that represent the overall possible questions to measure what they are designed to measure (Creswell,2012). Sekaran (2003) stressed that content validity guarantees that the measurement contains relevant representative items to capture the concept. They further mentioned that content validity of the instrument could be done via a panel of judges consisting of experts in the field of research.

The content validation procedure for this study began by creating the large pool of items, which were adapted from various sources (Netemeyer, Bearden, & Sharma,2003). Later on, the number of items in the pool was reduced based on the analysis of content validity. To determine the consensus among the experts, the

analysis of content validity was done using Content Validity Index (CVI). The CVI is the measurement of the item's appropriateness to represent certain construct under investigation (Polit, Beck, & Owen, 2007). Lynn (1986) suggested that three to ten experts should validate the content of the instrument.

This study choose five experts in IS and IT from UUM and UiTM to validate the instrument. Each of the experts was provided with sufficient information on the objectives, research questions, research model, and the instructions for CVI rating. All the experts have rated the instrument items based on 7 scales (1 to 3 = Least Important, 4 = Neutral, 5 to 7 = More Important) after taking the recommendations by Churchill (1979).

The CVI value was calculated based on each item (i-CVI) and the overall scale (s-CVI) (Polit et al., 2007). The acceptable cut-off point for i-CVI is 0.78 (Lynn, 1986). On the other hand, s-CVI can be calculated using s-CVI/UA (Universal Agreement method) and s-CVI/Ave (Averaging method). For this study, the s-CVI/Ave was chosen with the cut-off value 0.40 and above based on evaluation criteria for kappa values indicate that between 0.40 and 0.59 is fair, between 0.60 and 0.74 considered good and 0.74 and above considered excellent value (Fleiss, 1981; Cicchetti & Sparrow, 1981; Fleiss, Levin, & Paik, 2013). Table 3.7 summarizes the CVI analysis of the current study.

Table 3.7.
Analysis for Content Validity Index (CVI)

Dimension	Items	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	i-CVi	Evaluation
1) Complexity	1a	7	5	7	6	6	0.885	Excellent

2) Visibility	1b	7	5	2	7	6	0.771	Excellent
	1c	7	5	7	6	6	0.886	Excellent
	1d	7	5	7	7	6	0.914	Excellent
	1e	7	5	7	7	6	0.914	Excellent
	2a	3	4	6	7	6	0.743	Excellent
	2b	3	4	2	7	7	0.657	Good
	2c	6	4	6	7	7	0.857	Excellent
	2d	6	4	2	6	7	0.714	Good
	3a	6	4	2	7	7	0.743	Excellent
	3b	6	4	2	7	7	0.743	Excellent
3) Flexibility	3c	7	4	7	7	7	0.914	Excellent
	4a	7	4	6	7	7	0.886	Excellent
	4b	7	4	6	7	7	0.886	Excellent
	4c	4	4	2	7	7	0.771	Excellent
4) Clarity	5a	7	4	2	7	7	0.771	Excellent
	5b	7	4	2	7	7	0.771	Excellent
	5c	7	4	7	7	7	0.914	Excellent
	5d	7	4	7	7	7	0.914	Excellent
5) Manageability	6a	7	4	7	7	7	0.914	Excellent
	6b	7	4	7	7	7	0.914	Excellent
	7a	7	4	7	5	5	0.800	Excellent
6) Practicality	7b	7	4	7	5	6	0.829	Excellent
	7c	7	4	7	5	6	0.829	Excellent
7) Effectiveness								

7 d	7	4	7	5	6	0.829	Excellent
7e	7	4	7	5	7	0.857	Excellent

From the Table 3.7, after validating the items with 5 experts using content validity index, all the items are verified successfully. The i-CVI for all the items of the 7 dimensions ranged from 0.657 to 0.914. The overall s-CVI for the 26-item scale was 0.83 which indicated high content validity of the items for the construct of PKV model. Kappa statistic ranged from 0.83 to 1 for most of the items. 65% out of 26 items are considered “excellent” and accepted to be used for model measurement with i-CVi value more than 0.78 based on Polit et al. (2007). Two of the 26-items scale were rated as “good” evaluation range from 0.6 to 0.74 kappa coefficient indicate that the items are acceptable instrument for model measurement. The values still accepted based on Fleiss (1981) and Cicchetti & Sparrow (1981). As a conclusion from the validation of the verification instruments for PKV model all the 26 items from 7 dimensions are successfully validated by 5 experts and is accepted to be used for the PKV model verification purposes. Next section, PKV model verification are conducted by using the validated instruments as mentioned above.

3.11.2 Usability Testing

The testing instrument was used to evaluate the prototype in terms of visibility, flexibility, learnability, the application behavior and real-time decision making. Several open-ended questions were included in the instrument. This serves as a formative evaluation for the prototype. The open-ended questions were intentionally devised to obtain objective assessments. Table 3.8 presents the list of definitions according to the dimensions and source of references for the usability testing to evaluate the PKVS prototype.

Table 3.8.
Usability Testing Dimensions Definition

Dimensions	Definitions	Sources
1) Visibility	Display of information and interface design of the system. The ability to view the processes, transactions and other activities operating accurately and completely via using PKVS prototype.	Jooste et al., 2013 Lewis, 1995
2) Flexibility	Customizable and user control of the system. It is the ability of software to change easily in response to different user and system requirements.	Lin, Choong & Salvendy, 1997 Lewis, 1995
3) Learnability	Easy to learn. The ease with which a user can learn to operate, prepares inputs for, and interprets outputs of a system or component.	Lin, Choong & Salvendy, 1997 Lewis, 1995
4) Application Behavior	Measuring the system behavior in terms of enhance user efficiency through a consistently rapid response rate.	Jooste et al., 2013 Lin, Choong & Salvendy, 1997 Lewis, 1995
5) Real-time Decision Making	System ability to deliver live data, relevant data, and real-time data to support decision making process.	Jooste et al., 2013

3.11.2.1 Develop Usability Testing Instrument

The instrument, consisting of close-ended questions, was used to evaluate the prototype in terms of usability experiences to gain a deeper understanding of users' needs and experiences. The measurements were made through an instrument named Q-U, which comprises of five main dimensions, visibility, flexibility, learnability, application behaviour, and real-time decision making as usability attributes. A visibility determined how well the state of the system is conveyed to its users in

terms of data display, functionalities, organizations as well as navigation by using visualization (Jooste et al., 2013; Lewis, 1995). For flexibility was measured the ability of software response with different users, whilst learnability are measured the capability of a software product to enable the user to learn how to use it and it is a major concern in the design of complex software applications (Lin, Choong & Salvendy, 1997; Lewis, 1995). It was consisted of 27 questions, which are scaled by values from 1 to 5. Scale 1 equals to strongly disagree, scale 2 equals to disagree, scale 3 equals to neutral, scale 4 equals to agree and scale 5 equals to strongly agree. The overall Q-U instrument is finalizing and send to the respondents to answer all the questions after trying the PKVS prototype. The open-ended questions were devised so that the usability of the prototype can be objectively assessed. Table 3.9 presents the dimensions and definitions of usability testing instruments adopted in this study.

Table 3.9.
Usability Testing Dimensions and Its Definitions

Dimensions	Definitions	Questions	Sources
1) Visibility	Display of information and interface design of the system. The ability to accurately and completely view the processes, transactions and other activities operating via using PKVS prototype.	a) This system can display the information (virtual results) in a well-structured manner. b) All instructions are visible and self-explanatory. c) Navigation options in this application such as (Links, shortcuts, home, back, forward, etc) are displayed in visible manner. d) The data in this system concisely presented. e) This system has all functions and capabilities I expect it to have. f) I like the interface of this system. g) The interface for this system is pleasant. h) The organization of information in the system	Jooste et al., 2013 Lewis, 1995

2) Flexibility	Customizable and user control of the system. It is the ability of software to change easily in response to different user and system requirements.	screen was clear. a) I felt fully in control when using this system. b) This system has customizable feature. c) In this system the design for data entry is flexible. d) The data can be used, manipulated and/or processes in easy manner.	Lin, Choong & Salvendy, 1997 Lewis, 1995
3) Learnability	Easy to learn. The ease with which a user can learn to operate, prepares inputs for, and interprets outputs of a system or component.	a) In this system the data grouping reasonable for easy learning. b) In this system promotes learnability to make it accessible for infrequent usage. c) In this system, the grouping of menu options is logical. d) I believe I could become productive quickly using this system.	Lin, Choong & Salvendy, 1997 Lewis, 1995
4)Application Behavior	Measuring the system behavior in terms of enhance user efficiency through a consistently rapid response rate.	a) This application enhances user efficiency through a consistency rapid response rate. b) The application behavior is consistent. c) The information was effective in helping me complete the tasks. d) It was easy to find information I needed. e) Whenever I made a mistake using the system, I could recover easily and quickly. f) I was able to complete the tasks quickly using this system.	Jooste et al., 2013 Lin, Choong & Salvendy, 1997 Lewis, 1995
5)Real-time	System ability to deliver live data,	a) system This provides the information visualization	Jooste et al.,

Decision Making	relevant data, and real-time data to support decision making process.	functionality (comparison charts, graphs to reveal trends etc) to assist in decision making. b) In this system, the breadth and depth of the data provide sufficient coverage for all data resources. c) In this system, data is received on time to take suitable actions and decisions. d) In this system, the data is always live data and up to date. e) In this system, the data was cleaning, cleansing and profiling, so there are almost no errors in the data.	2013

As stated previously, this study adapts the existing instruments to measure prototype usability. Therefore, to gather relevant items for the constructs, various existing questionnaires were studied and come out with the first draft of the instrument and will validate in the next sections.

3.11.2.2 Validate Usability Testing Instrument

For validating the instrument of PKVS prototype, a content validity was conducted. The content validation procedure for this study began by creating the large pool of items from usability instruments, which were adapted from various sources (Jooste et al., 2013; Lin, Choong & Salvendy, 1997; Lewis, 1995). Later on, the number of items in the pool was reduced based on the analysis of content validity. To determine the consensus among the experts, the analysis of content validity was done using Content Validity Index (CVI). This study chooses three experts in IT from different university to validate the PKVS instrument based on suggested by Lynn (1986) and Nielsen (1994). Each of the experts was provided with sufficient information on the PKVS prototype objectives, the flow the prototype, every functions of PKVS

prototype and the instructions for CVI rating. All the experts have rated the instrument items based on 7 scales (1 to 3 = Least Important, 4 = Neutral, 5 to 7 = More Important) after taking the recommendations by Churchill (1979) and Chiva et al. (2006).

The CVI value was calculated based on each item (i-CVI) and the overall scale (s-CVI) (Polit et al., 2007). The acceptable cut-off point for i-CVI is 0.78 (Lynn, 1986). On the other hand, s-CVI can be calculated using s-CVI/UA (Universal Agreement method) and s-CVI/Ave (Averaging method). For this study, the s-CVI/Ave was chosen with the cut-off value 0.40 and above based on evaluation criteria for kappa values indicate that between 0.40 and 0.59 is fair, between 0.60 and 0.74 considered good and 0.74 and above considered excellent value (Fleiss, 1981; Cicchetti & Sparrow, 1981). Table 3.10 summarizes the CVI analysis of the current study.

Table 3.10.
Analysis for Content Validity Index(CVI)

Dimension	Items	Expert 1	Expert 2	Expert 3	i-CVI	Evaluation
1) Visibility	1a	7	7	7	1.00	Excellent
	1b	7	7	7	1.00	Excellent
	1c	7	7	7	1.00	Excellent
	1d	7	7	7	1.00	Excellent
	1e	7	7	7	1.00	Excellent
	1f	7	7	7	1.00	Excellent
	1g	7	7	7	1.00	Excellent
	1h	7	7	7	1.00	Excellent
2) Flexibility	2a	5	6	7	0.86	Excellent
	2b	6	6	7	0.91	Excellent
	2c	5	5	5	0.71	Good

	2d	6	7	6	0.91	Excellent
3) Learnability	3a	6	6	6	0.86	Excellent
	3b	7	7	7	1.00	Excellent
	3c	7	6	7	0.95	Excellent
	3d	7	7	7	1.00	Excellent
4) Application Behavior	4a	6	6	7	0.91	Excellent
	4b	7	6	7	0.95	Excellent
	4c	7	7	7	1.00	Excellent
	4d	7	7	7	1.00	Excellent
	4e	7	7	7	1.00	Excellent
	4f	7	7	7	1.00	Excellent
5) Real-time decision making	5a	7	7	7	1.00	Excellent
	5b	5	6	5	0.76	Excellent
	5c	7	7	6	0.95	Excellent
	5d	5	6	6	0.81	Excellent
	5e	5	5	7	0.81	Excellent

From the Table 3.10, after validating the items with 3 experts using content validity index, all the items are verified successfully. The i-CVI for all the items of the 5 dimensions ranged from 0.71 to 1. The overall 51% of the i-CVI for the 27-item scale was 1.00 which indicated high content validity of the items for the construct of PKV model. 96.30% out of 27 items are considered “excellent” and accepted to be used for model measurement with i-CVi value more than 0.74 based on Polit et al. (2007). Only one of the 27-items scale were rated as “good” evaluation range from 0.6 to 0.74 kappa coefficient indicate that the items are acceptable instrument for model measurement. The values still accepted based on Fleiss (1981) and Cicchetti & Sparrow (1981). As a conclusion from the validation of the PKVS prototype

instruments, all the 27-items from 5 dimensions are successfully validated by 3 experts and is accepted to be used for the PKVS prototype validation purposes. Next section, PKVS prototype validation are conducted by using the validated usability testing instruments as mentioned above.

3.11.3 Expert Review for Knowledge Base Validation

The finalize PKV model and PKVS prototype testing instrument was used to evaluate the PKV model in terms of correct data representation, usability, decision support and knowledge base. Several open-ended questions were included in the instrument. A correct data representation was measured using visual appeal, simplicity, organization, and understandability (Chi, Diehl & Norman, 1998), whilst usability used perceived usefulness, ease of use, and learnability (Leventhal & Banres, 2008; Brooke, 1996; Nielsen, 1994). For decision support system are measured based on data exploration and how the visual representation can support decision making process and for knowledge base was measured based on the overall dimensions stated (Mikulakova et al., 2010). This knowledge base is the conclusion of the three dimensions and it is the interpretation of the whole PKV model and PKVS prototype evaluation. The open-ended questions were intentionally devised to obtain objective assessments. Table 3.11 presents the list of definition according to the dimensions and source of references of the knowledge base validation for the expert review.

Table 3.11.
Expert Review for Knowledge Base Validation

Dimensions	Definitions	Sources
Correct Data Representation	Represent the visual appealing, simplicity, well organization of data and how it can attracts viewers	Chil, Diehl, & Norman(1988)

Usability	The usability based on perceived usefulness, ease of use and learnability.	Brooke (1996), Nielsen (1994), Leventhal & Barnes (2008)
Decision Support	The decision support system based on the data exploration process reveals insightful information.	Shneiderman & Plaisant (2010); Tory & Moller (2005); Lam et al., (2012)
Knowledge Base	The interpretation of decision making based on the knowledge base produced.	Mikulakova et al., 2010

3.11.3.1 Develop Knowledge-based Instruments

The objective of this stage is to validate the PKV model as well as PKVS prototype in the context of decision making process. The main instrument used for this review is a questionnaire which adapted from previous studies Syamsul (2011). In this questionnaire is contains 23 questions from four (4) dimensions which are:- (1) correct data representation, (2) usability, (3) decision support system, and (4) knowledge base. Along with that, few demographic questions were also asked like gender, highest level of education and how many years of experience. Table 3.12 summarized all the items from each dimensions. Next section will explain in details the experts to validate the knowledge-based of the PKV model.

Table 3.12.
Items for Model Validation

Dimension	Items	Source(s)

1) Correct Data Representation	a) It highlights important information.	Chiel, Diehl & Norman, 1988.
	b) It simplifies the data representation.	
	c) The data shown after exploration attracts my interest.	
	d) The presented information is well organized.	
	e) I can understand the information represented at a glance.	
2) Usability	a) I would like to use the system frequently.	Brooke (1996); Nielsen
	b) I found the system simple.	
	c) The system was easy to use.	
	d) I would need the support of a technical person to be able to use this system.	
	e) I found the various functions in the systems well integrated.	Leventhal & Barnes (2008).
	f) The system operation was consistent.	
	g) I imagine that most people would learn to use this system quickly.	
	h) I felt confident using the system.	
	i) The system has the functions and capabilities I expect it to have.	
	a) The visual representation supports the data insight.	Tory & Moller
3) Decision Support System	b) Exploration functions (filtering and extracting information) are consistent with needs.	
	c) The system presents the hidden information.	(2005); Lam et al. (2012).
	d) The data exploration process reveals insightful information.	
	e) The system well-structures the presented information.	Baker et al. (2002)
	f) The information presented meets my goal of using the system.	
	g) The system supports decision making.	
4) Knowledge Base	a) How u can interpret the result?Is it valid to be use in DM process to improve student performance.	Mikulakova et al., 2010
	b) From 1 to 10, how can u validate the result?	

3.11.3.2 Validate Knowledge-based Instruments with Experts

After conducting knowledge-based from prescriptive analytic, the evaluation was conducted with face validity. Three (3) experts from IHL decision and policy makers

is given access to the web-based PKVS prototype. The briefing to guide the users is done through online conference meeting. The users are given 1 to 5 scale to determine how the prototype and model are organized. The results will explain in the next section. The open ended questions are analysed using Elo and Kyngas' (2008) content analysis approach for qualitative data. The demographic profiles of the participants explain in Table 3.13.

Table 3.13.
Demographic Profiles of Experts in Model Verification

No.	Qualifications	Gender	Expertise	Year of Experience
1	PhD in Computer Science	Male	Information System, Analytics	30 years
2	PhD in Software Engineering	Male	Data Warehousing, Intelligent Database, Data Structures	32 years
3	PhD in Computer Science	Female	Machine Learning, Data Mining, Predictive Analytics	24 years

Based on the table above, the experts have more than 24 years' experience in IHL administration especially as policy maker. The years of experience shows that the expertise are well experienced in handling students' data related decision making in IHLs.

3.12 Summary

This chapter presents an overview of the research methodology applied in this study. The study utilized the quantitative method by applying three analytics approaches to achieve the objectives of this study. SPSS was used for the descriptive and predictive analyzed analyses, while WEKA was applied in the data mining process that represents the prescriptive analysis.

In verifying the proposed model, two validation methods were conducted; expert review and usability testing. These methods were useful as they provide extensive reviews from different perspectives. All the results were examined in order to revise the proposed model. Thus, the final version of the proposed model was formalized. Besides, these outcomes serve to support the objectives one and two of the study. To examine whether the expectation in objective three is achieved, this study has developed a prototype based on the PKV model and prototype, which were validated through usability testing. The validation also done by using expert review techniques for decision maker to evaluate the PKV model and PKVS prototype.

CHAPTER FOUR

MODEL DEVELOPMENT

4.1 Introduction

This chapter provides the research framework for the study according to the background discussed in the literature review. The main purpose is to propose a model for Prescriptive Knowledge Visualization (PKV) based on Internet use behavior (IUB) to improve students' academic performance. The model was formulated based on the related theories as described in the previous chapter.

4.2 Theoretical Background for Designing PKV Model

Various theories and models were reviewed to develop the conceptual model for this study as shown in Figure 4.4. The model is based on the DIKW model (Ackoff, 1989), also known as the data-information-knowledge-wisdom hierarchy, Knowledge Generation Model, a Visual Analytic Model, developed by Sacha (2014), and Human Cognition Model by Green et al. (2009). Other theories used include Process Visualization Theory (PVT) introduced by Overby (2008,2010), Cognitive Load Theory (CLT) was developed by John Sweller 1988, and Decision-Making Theory (DMT) as proposed by Simon (1979). In the following sections, the common elements of the aforementioned elements are described in detail.

4.2.1 DIKW (Data, Information, Knowledge and Wisdom) Model

The Data-Information-Knowledge-Wisdom (DIKW) model or DIKW pyramid, developed by Ackoff (1989), is an often-used method originated in knowledge management (KM) to explain the ways data (D) moved to information (I), knowledge (K), and wisdom (W) with a component of actions and decisions. The model looks into various ways of extracting insights and value from all sorts of data.

The DIKW is a popular model for classifying human understanding regarding perceptual and cognitive space. Even though, there is a large volume of published studies on the role of DIKW as shown in Figure 4.1, the descriptions only focus on the three hierarchy levels, data, information, and knowledge, neglecting the function of wisdom.

In the context of DIKW, data represents a collection of facts in a raw or unorganized form, such as numbers or characters. However, without a context, data is meaningless. Information is the next building block of the DIKW Pyramid. Information refers to data that has been cleaned from errors and further processed to ease the measurement, visualization, and analysis of a specific purpose. Depending on the particular purpose, data processing may include different operations, such as combining different sets of data (aggregation) to ensure that the collected data are relevant and accurate (validation). Data are usually organized in a way that exposes the relationships between various seemingly disparate and disconnected points. By asking relevant questions in the form of ‘who’, ‘what’, ‘when’, and ‘where’, valuable information derived from data can be more useful. Once the question focuses on ‘how’, the information will leap to knowledge.

Knowledge, the next entity in the DIKW hierarchy, is defined as actionable information (Tiwana, 2002). The main difference, as highlighted in knowledge management, is that knowledge triggers action. Specifically, the questions can be constructed in three ways; (i) “How” is the information, derived from the collected data; (ii) “How” are the pieces of this information connected to others to add more meaning and value; and, (iii) “how” can the information achieve a goal. All these questions will lead to the creation of knowledge. Hence, instead of just viewing it as a description of collected facts, the understanding of applying it to achieve specific

goals will transform information into knowledge. Deeper insights discovered from the relationships that are not explicitly stated as information enable the movement to the next level of the DIKW pyramid. After the knowledge and insights gained from the information are used to take proactive decisions, the final level of the pyramid, wisdom is reached.

To get to top of the DIKW hierarchy, the questions, such as ‘why do something’ and ‘what is best’ should be answered. In other words, wisdom refers to knowledge applied in action. Wisdom accompanies knowledge and allows one to make the best choices. In short, if data and information reflect past incidents, knowledge and wisdom are associated with history to be achieved in the future. Figure 3.1 illustrates the DIKW model by Ackoff.

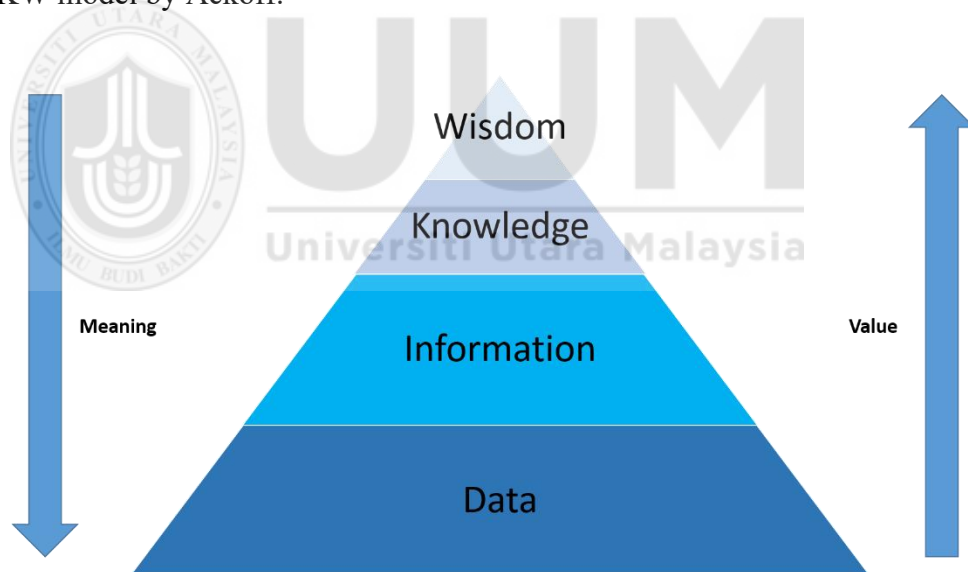


Figure 4.1. Data-Information-Knowledge-Wisdom (DIKW) Model (Ackoff, 1989)

As shown in Figure 4.1, the DIKW Pyramid represents the relationships between data, information, knowledge, and wisdom. Each block represents a higher level from data to information to knowledge and finally to wisdom. Each level answers different questions about the initial data and adds value to it. The model is still being used in many forms to extract value and meaning as it represents a simple and thus strong metaphor. Data with deeper meaning and context provide more knowledge

and insights that facilitate better, informed, and data-based decisions. The first bottom level consists of big size data with low meaning. In a digital universe that is growing exponentially, most of the unstructured data have no meaning and value. However, once transformed into information, not only the size becomes smaller, but the data will also be meaningful and valuable. Next, in responding to the “how” question, the information will be converted to knowledge, which becomes more valuable and focus in providing insight. Bellinger et al. (2004) further elaborated Ackoff’s exposition by suggesting that the conversion of information to knowledge involves patterns’ understanding, known as cognitive. The value increases while the meaning decreases as knowledge already represents valuable action. Wisdom is achieved by assimilating and applying knowledge to make the right decisions. At this stage, the value of knowledge highly increases as successful decision involves principles of understanding.

Based on the above discussions, this study attempts to apply all the DIKW components in the development of the PKV model, starting from data up to wisdom. In essence, the aim of the DIKW model is to enhance the understanding of how information evolves and is utilized to make informed decisions, emphasizing the importance of knowledge and wisdom in the process. However, this model only focus the hierarchy of DIKW in general, but does not highlight on how the hierarchy can be articulated explicitly. It is important to note that the need of visualization helps convey the sequential flow from data to wisdom (Akhtar, Tabassum, Perwej & Perwej, 2020), it still simplifies the complexity of real-world information processing. In reality, when using the DIKW model and its visual representation, this visualization illustrates that as we move up the pyramid, the level of cognitive and understanding increases. In summary, visualization components added in this model

that would enhance the DIKW model's effectiveness as an articulation tool, aids in understanding its concepts, and provides valuable insights into information processing and understanding. By visualizing data, trends, and relationships, one can gain a deeper understanding of the underlying knowledge and potentially derive wisdom from it. Other related models are discussed in details in the following section.

4.2.2 Knowledge Generation Model for Visual Analytics

The Knowledge Generation Model for Visual Analytics created by Sacha et. al (2014) represents another basis for developing the PKV. The model, as shown in Figure 4.2, comprises four components; Data, Models, Visualization, and Knowledge. This model can be seen as an integral approach combining visualization, human factors, and data analysis. It is split into two parts with the model consists of a computer and human parts. Visual analytics is allowing direct human interaction with various tools to produce insights, draw conclusions, slice-dice information in real time, and facilitate better decision-making. All the components will be explained in details.

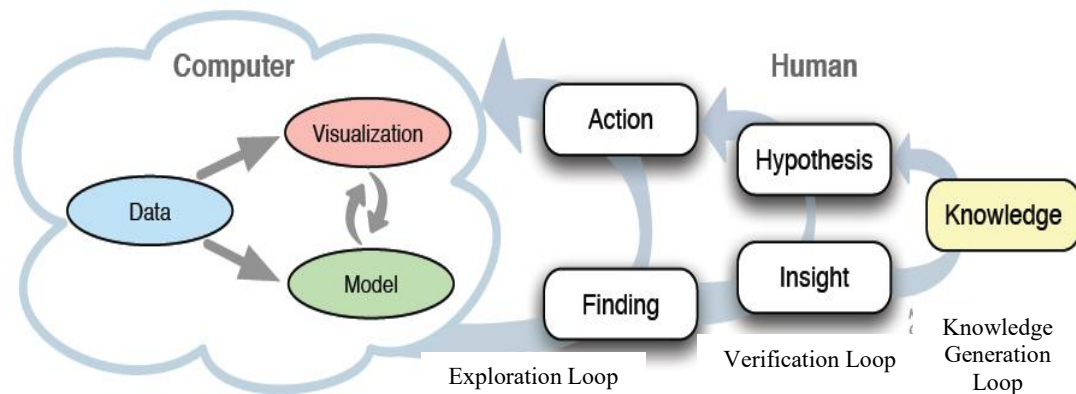


Figure 4.2. Knowledge Generation Model for Visual Analytics (Sacha et al., 2014)

The details of Knowledge Generation Model for Visual Analytics are illustrated in Figure 4.2. The left side of the model refers to the computer part that contains data, visualization, and model. The computer part represents the visual analytics system

while the human indicates the knowledge generation process. To generate knowledge, human will go through the reasoning process through exploration and verification. The next subsection will elaborate in details the components that involve to develop PKV conceptual model. The elaborations will start from computer, followed by human subcomponents.

4.2.2.1 Computer

Computer part represents the visual analytics system. The starting point of all the visual analytics systems is data that must be representative and related to specific problem. The processes include creating, gathering, and selecting data to determine its quality. More data can be created during the analysis using automated methods (e.g., clustering or classification) or manual annotations. Hence, original information containing details about the data creation, gathering, selection, and preprocessing are important to estimate the trustworthiness of the analyzed results.

Models can be as simple as descriptive statistics describing a property of a subset of data or as complex as a data mining algorithm. The Knowledge Discovery in Databases (KDD) process leads the data modelling. Complex patterns or abstractions identified by data mining methods can be used in visualizations by showing, for instance, clustering or classification results. In addition, the automatically created model can be analyzed or visualized to derive insights.

A different path from data to knowledge is the information visualization pipeline using data visualizations. Visualizations use data or models generated from the data that enable analysts to detect relationships in the data. In visual analytics, visualizations are often based on automatic models, such as the clustering models, which are used to group data. In addition, a model itself can be visualized, for

instance, a box plot showing the data distribution of a dimension. Visualization methods for a model may vary depending on the state of the visualization. For example, in semantic zooming, a visualization might use different properties of a model depending on the zoom level. Visualization is often used as the primary interface between analysts and visual analytics systems whereas understanding the model often requires more cognitive efforts.

In this study, all the three components in the computer part are pertinent to develop the PKV model. The combination of data, model, and visualization is comprehensive while at the same time compatible to help domain experts to explore large and complex data sets as suggested by Keim et al (2008). Data serves as the foundation for knowledge visualization. It contains the information and insights that need to be conveyed to the users. To help extract patterns, identify trends, and uncover insights from the data models take place to facilitate the mapping of data to visual elements, enabling the creation of meaningful visual representations. Then the function of Visualizations enhance human cognition by leveraging our visual perception capabilities, enabling users to quickly identify patterns, trends, and relationships within the data by using visual elements. By leveraging these three components in develop PKV model will facilitates effective communication, data exploration, pattern recognition, decision support, and knowledge discovery. It empowers users to gain deeper insights, make informed decisions, and uncover hidden relationships within complex datasets, ultimately enhancing understanding and facilitating innovation in various domains. The subsequent section elaborates in details the function of the human parts.

4.2.2.2 Human

The human part of the Knowledge Generation models the cognitive processes associated with an analytical session processed in the computer part. The model indicates that there is no clear separation between the computer and human, as both parts are required for data analysis. The only missing is the creativity of human analysis to allow the creation of surprises, which are often subtle or hidden in connecting between data and problem domain. The only limitation is the inefficiency and ineffectiveness in handling a large amount of data. In visual analytics, human and computer are connected through the former's interaction and perception abilities.

Hence the current study incorporates the human cognitive and reasoning elements in the development of the PKV model to interpret knowledge (Green et al., 2008; Kwon et al., 2011; Brehmer & Munzner, 2013; Pirolli & Card, 2005; Norman, 2002).

4.2.2.3 Reasoning

The reasoning part of this model relates to the human capabilities to explore, verify, and generate knowledge based on the visual analytics process (computer). The exploration loop describes how analysts interact with a visual analytics system to generate new visualizations or models and analyze the data. Analysts explore data supported with the visual analytics system by interacting and observing the feedback. Actions taken in the exploration loops are dependent on findings or a concrete analytical goal. Actions naturally provoke interactions of analysts with visual analytics systems. Actions taken to create models are summarized as model building actions, which in turn are related to the KDD process and its configuration. A finding is an interesting observation made by an analyst using the visual analytics system. The finding leads to further interaction with the system or to new insights. The actions and findings in the exploration loop are closely related to the visual analytics

systems. Analysts gain a new insight when they are able to understand the findings and interpret them in the context of the problem domain.

The verification loop guides the exploration loop to confirm hypotheses or form new ones. To verify a concrete hypothesis, a confirmatory analysis is conducted, and the exploration loop is steered to reveal findings that verify or falsify the hypothesis. Analysts gain insights when they can interpret findings from the exploration loop in the context of the problem domain. Insights may lead to new hypotheses that require further investigation. Analysts will obtain additional knowledge when they assess one or more trustworthy insights.

Hypotheses are constructed based on an analyst's knowledge of a problem domain. New knowledge is then acquired by formulating and verifying the hypotheses. When the analyst trusts the insights, it may also influence the formulation of new hypotheses.

In this study, the reasoning plays a fundamental role in the process of knowledge generation within a knowledge generation model. It serves as a cognitive process that allows individuals to make sense of information, draw conclusions, and generate new knowledge based on existing knowledge and evidence. Reasoning can be seen as the engine that drives the acquisition, integration, and transformation of knowledge.

A knowledge generation model typically involves several stages, such as observation, information gathering, analysis, synthesis, and evaluation. Reasoning is interwoven throughout these stages, enabling individuals to make logical connections, form hypotheses, identify patterns, and draw inferences.

In summary, reasoning is integral to the entire process of knowledge generation within a knowledge generation model. It enables individuals to make sense of

observations, gather and evaluate information, analyze and synthesize data, and critically assess the knowledge generated. Reasoning is a cognitive process that supports the acquisition, integration, and transformation of knowledge, ultimately leading to the generation of new insights and understanding. Without reasoning, the PKV model would lack the ability to extract meaning, connect concepts, and derive valuable insights from the available information and knowledge. Hence, it is importance to combine the reasoning in this study to produce knowledge and wisdom for making wiser decision.

Despite the advantages of this model in handling data exploration, analysis and decision-making, it also comes with some challenges and limitations. This model bring user be open to interpretation that will lead to potential misinterpretations if users lack a clear understanding of the data. That is where the need of prescriptive analytic to integrate with this model to overcome these challenges. Combining this model with prescriptive analytic enables data-driven, informed decisions based on historical trends and future predictions. The knowledge generation process can be influenced by human biases, both in data selection and analysis, and in the interpretation of visualizations. It is essential to be aware of and address these biases by integrating prescriptive analytic that provides data-driven recommendations for decision-makers, that will ensuring objective and evidence-based choices. Next section will explain the other base model in developing the PKV model.

4.2.3 Human Cognition Model

The Human Cognition Model (HCM) proposed by Green et al. (2009) is another suitable model applied in this study. This goal of this model is to revolutionize the cognition in the visualization design. A major problem in visual analytics is that human cognition is often assumed to be an over simplified black box. In HCM, five

components were introduced that can be derived from the models' use. The details of the HCM and all the five components are illustrated in Figure 4.3.

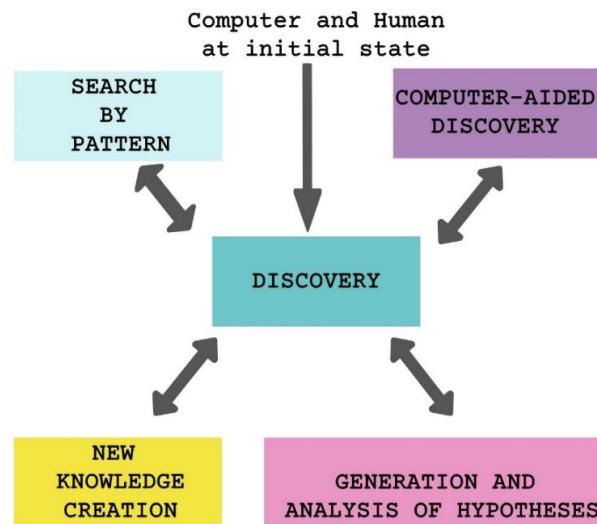


Figure 4. 3. Human Cognition Model (Green et al., 2009)

Figure 4.3 explained the five components of the HCM; discovery, computer-aided discovery, generation and analysis of hypotheses, new knowledge creation, and pattern search.

Discovery is the key element that describes the overall process of HCM. In handling the overwhelming semantic data points, information is presenter according to relevant context using the human cognitive overload mitigation method. The direct interaction between human and visualized information focuses on discovery. The model also includes guidelines for discovery and knowledge building. The cognition of relevant patterns and schema derived from knowledge and insights plays a central role in the human part of this model.

An extension of the knowledge building process that holds great potential for multi-modal visualization is the creation of hypotheses. Generating hypothesis generation can be influenced by cognitive bias as individuals tend to look for evidence on what they already or want to believe. Getting over such biases can be time consuming and

destructive to the process. The analysis starts by proving and disproving a list of hypotheses based on respective evidences (Heuer, 1999). The list of hypotheses is determined by human, while the evidences are by computer. The computer, with its superior working memory, creates a weighted matrix that will be edited by human who has superior reasoning skill. Although human initiated the hypotheses, the computer plays a significant role in shortening the process by providing a more solid conclusion.

Based on the advantageous of the elements in human cognition model that has been described, human cognition model is suitable to be used as a base model in PKV models because it provides a comprehensive understanding of how individuals process information, make decisions, and solve problems. Prescriptive models aim to guide and optimize human performance by providing recommendations or guidelines for achieving desired outcomes. By incorporating the insights from the human cognition model, prescriptive models can leverage the power of human cognitive processes to enhance decision-making, problem-solving, and overall performance.

Here are some reasons why the human cognition model is suitable for PKV model:

Realistic representation of human capabilities: The human cognition model captures the complexity and nuances of human cognitive processes. By integrating this understanding into PKV model, it can ensure that the recommendations provided are aligned with human capabilities, taking into account limitations, biases, and cognitive strategies employed by individuals. This realistic representation enhances the feasibility and effectiveness of the prescribed actions.

Optimization of decision-making and problem-solving: The human cognition model provides insights into how individuals reason, analyze information, and make

decisions. PKV models can leverage this knowledge to optimize decision-making processes by suggesting systematic approaches, highlighting potential biases, and providing frameworks for evaluating alternatives. Similarly, the understanding of problem-solving strategies can help design prescriptive models that guide individuals towards effective problem-solving techniques and promote innovation.

Personalization and adaptability: The human cognition model recognizes that cognitive processes can vary among individuals due to factors like prior knowledge, expertise, and cognitive styles. PKV models that incorporate the human cognition model can be personalized to account for these individual differences, tailoring recommendations to suit specific needs and capabilities. Additionally, the dynamic nature of the human cognition model allows prescriptive models to adapt and adjust recommendations based on real-time feedback and changing circumstances.

Cognitive support and augmentation: PKV models based on the human cognition model can act as cognitive aids, providing support and assistance to individuals during complex decision-making tasks or problem-solving situations. These models can offer prompts, reminders, and guidelines that align with cognitive processes, helping individuals overcome cognitive limitations and enhance their performance. Such cognitive support can be particularly valuable in high-pressure or time-constrained environments.

In summary, by integrating the human cognition model into PKV models, it can harness the power of human cognitive processes to guide and optimize decision-making, problem-solving, and performance (Novaes, 2020; Maitland, & Sammartino, 2015). These models can be designed to accommodate individual differences, provide cognitive support, and adapt to changing circumstances. Ultimately,

incorporating the human cognition model into PKV enhances the applicability, effectiveness, and user-friendliness of the recommended actions or interventions.

Even though the human cognition model was used as the foundation for the development of the PKV model, it has significant flaws in terms of decision-making because of inborn cognitive biases and constraints. Humans can only process a certain amount of information at once because they have finite cognitive resources (Wang, 2021). Due to this restriction, important facts may be missed or only a small portion of the pertinent data may be taken into account. By leverage the cognitive component that consist of human interaction elements into the human cognition model, it will recognize the dynamic interplay between cognitive processes, human decision-makers, and the broader decision-making context. Thus, the enhanced elements embed the critical thinking, collaboration, emotional intelligence, and ethical considerations in achieving more effective and informed decision-making outcomes. Understanding and minimizing cognitive biases, fostering critical thinking, and utilizing data-driven approaches can help decision-makers make better decisions and get better results. By incorporating decision support systems through the use of prescriptive analytic can also support compensating for individual cognitive limitations and promote more effective decision-making. The conceptual of the PKV model will be covered in detail in the following section.

4.3 Prescriptive Knowledge Visualization (PKV) Model

In this section, the initial version of the proposed model is discussed. The model was developed based on the combination of all the components that were mentioned in sections 4.2.1 to 4.2.3. Figure 4.4 shows the first version of PKV model. The conceptual model of the study is developed based on the three models. The model

comprises three major components (Visualization, Analytics, and human interaction) with eight (DV, InfoVis, KV, WV, descriptive, predictive, prescriptive, and cognitive/reasoning) subcomponents. In this study, the model is developed to determine students' academic performance based on their IUB. Recommendation and solution are formulated using an enhanced prescriptive analytics method.



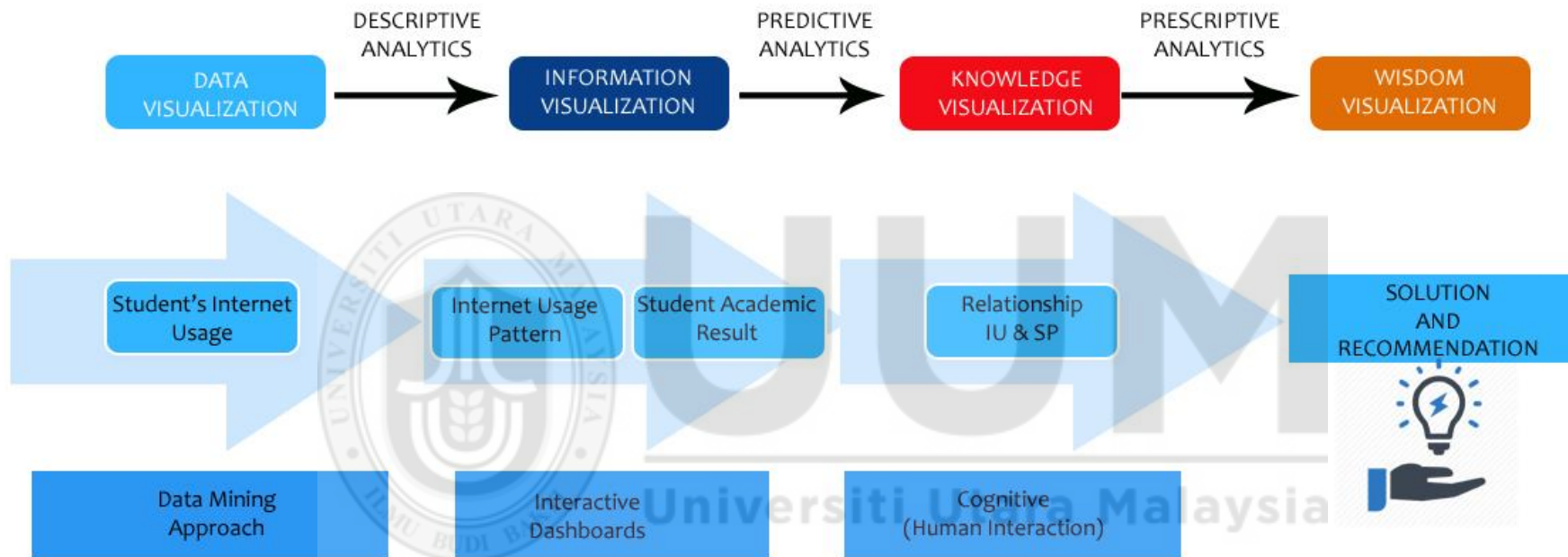


Figure 4.4. The PKV Conceptual Model of the Study

The PKV model is split into three components; visualization, analytics, and human interaction. The visualization consists of DV, InfoVis, KV, and WV. The analytics comprises descriptive, predictive, and prescriptive, while human interaction, known as cognitive is associated with reasoning components to produce human action. The goal is to develop a complete model by integrating an automated data analytics approach with interactive visualization to produce solution and recommendation that lead to action (wisdom visualization). To date, previous studies have proposed a series of conceptual frameworks that characterize the interplay between these approaches (Endert et al., 2014, Sacha et al., 2014, Amershi, 2014; Keim et al, 2008). However, these frameworks were mostly designed following the visualization perspective, focusing on computer interaction. This indicates that a strong connection between the computer (visualization and analytic) and human (cognitive and reasoning) interaction is still largely missing. Therefore, a deeper focus on such supportive interaction is highly required. The proposed model opens the perspective for new ways of combining automated and interactive methods, which will lead to more tightly integrated and ultimately more effective data analysis systems. Figure 4.5 shows the overview PKV model based the three models.

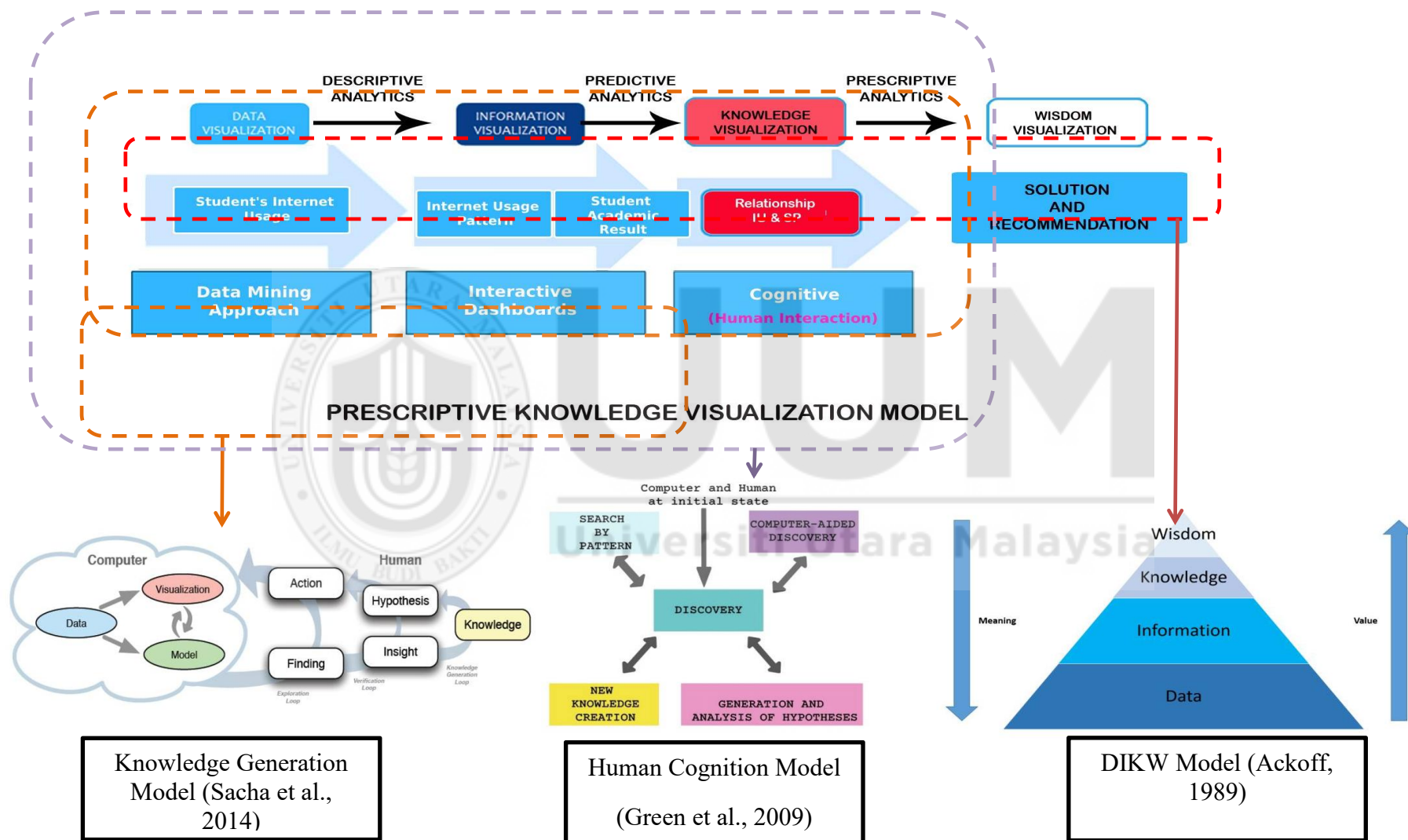


Figure 4.5. The PKV Conceptual Model (Combination with the base model)

4.3.1 Visualization Components

The terms used significantly in visualization include data, information, and knowledge (Cheney-Lippold, 2017). This represents a popular model for classifying human understanding and indicating different levels of abstraction, understanding, or truthfulness. Visualization is concerned with exploring data and information (Janicke, 2007). The visualization structure to construct the PKV model is based on the DIKW hierarchy established by Ackoff (1999). This study includes four subcomponents of visualization that will be discussed in the upcoming sections.

4.3.1.1 Data Visualization (DV)

Visualization starts with Data Visualization (DV). DV is an ancient need since the human mind is very visual. Therefore, massive amounts of data should be presented in an accessible and understandable manner. As organizations generate data every day, the availability of data on the Web keeps on increasingly tremendously, which makes it difficult for users to visualize, explore, and use. The ability to visualize data is crucial to scientific research. Figure 4.6 illustrates an data visualization process. In this pipeline is a basic information for visualization where at this stage the data haven't been processed and it directly view the user. Whatever the graphic present to the user is the raw data and has no meaning.

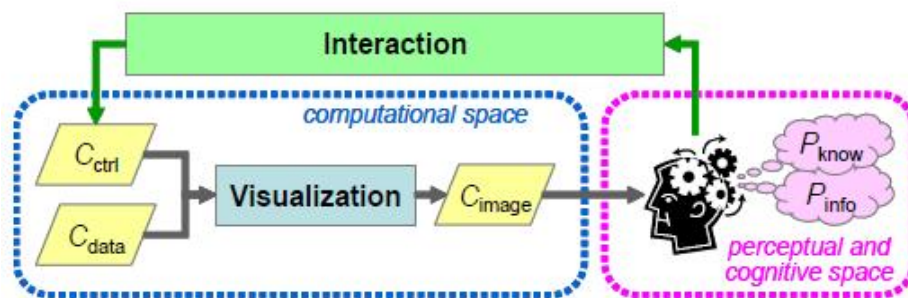


Figure 4.6. A Data Visualization Pipeline

Today, computers can be used to process large amounts of data. Data visualization is concerned with the design, development, and application of computer-generated graphical representation of the data. It provides effective representation of data originating from different sources. This enables decision makers to see analytics in visual form and makes it easy for them to make sense of the data. It also helps them discover patterns, comprehend information, and form an opinion.

Since the past two decades, emphasis has been placed on improving the speed of visualization tools, so that users can perform the interactive search faster, explore bigger parameter space, and find satisfactory results quicker. However, due to the growing amount of data and increasing availability of different visualization techniques, the search space for a visualization process is also getting larger and larger. Similar to the internet search problem, interactive visualization alone is no longer adequate. Therefore, there InfoVis is required to overcome the weaknesses of DV. Next section will explain on the second hierarchy in DIKW model which is Information Visualization (InfoVis).

4.3.1.2 Information Visualization (InfoVis)

In recent years, an assortment of techniques was introduced for visualizing complex features in data by relying on information abstracted from the data. Figure 4.7 illustrates an InfoVis process.

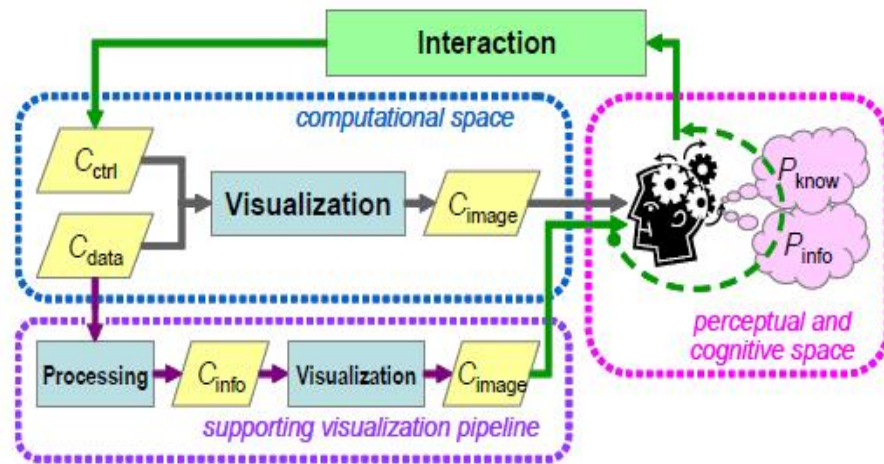


Figure 4.7. An Information Visualization Pipeline

In an information-assisted visualization, the user is provided with a second pipeline, which typically displays the information about the input dataset. It can also present the visualization process attributes, results properties, or characteristics of the user's perceptual behaviors. The user uses such information to reduce the 'search' space for optimal control parameters, hence making the interaction much more cost-effective. Such techniques provide an intrinsic interface between the scientific and information visualization communities. With the increasing size and complexity of data, the use of information to aid visualization will inevitably become a necessity rather than an option.

4.3.1.3 Knowledge Visualization (KV)

Eppler (2004) defined knowledge visualization as using visualization to transfer information into knowledge. However, the aim is to improve the transfer and creation of knowledge among people by giving richer means of expressing what they know. InfoVis and KV are both exploiting human innate abilities to effectively process visual representations. However, the way of using these abilities is different. While InfoVis typically helps to improve information retrieval, access, and

presentation of large data sets, KV primarily aims at augmenting knowledge-intensive communication between individuals.

In a visualization process, knowledge is essential. For instance, a user may assign specific colors to different objects in visualization according to certain domain knowledge. The user may also choose certain viewing positions because the visualization results can reveal more meaningful information or problematic scenario that requires further investigation.

Lack of certain knowledge would be the major obstacle for a user in deploying visualization techniques. For example, the user may not have adequate training on specifying transfer functions sufficient time, or navigation skills to explore all viewing positions possibilities of. Thus, both scenarios suggest the need for KV. The objectives of KV include sharing the domain knowledge between users and reducing their burden in understanding complex visualization techniques. It also enables the visualization community to not only learn and model best practices but also develop powerful visualization infrastructures evolutionarily.

Some of the general or domain knowledge has already been incorporated into various visualization systems, intentionally or unintentionally. For example, a default transfer function in a volume visualization system may capture the domain knowledge about a specific modality. If one could collect a large repository of such knowledge, it would be possible for a visualization system to choose an appropriate transfer function according to the information about the input datasets. Figure 4.8 shows a visualization pipeline supported by a knowledge base, which stores the knowledge representations captured from expert users. Rule-based reasoning can be utilized to establish an appropriate set, or several optional sets, of control parameters,

which can significantly reduce the ‘search’ space, especially for inexperienced users. The system component for cognitive and reasoning is commonly referred to as an inference engine in knowledge-based or expert systems. The shortcomings of such systems include the difficulties in specifying comprehensively what knowledge to capture and the inconvenience in collecting knowledge from experts. This represents the limitations of deploying such systems to specific application domains.

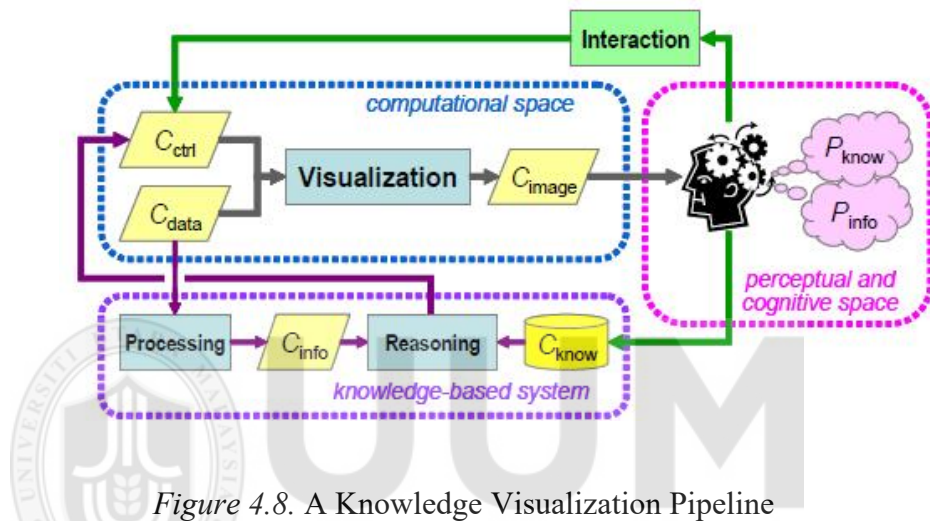


Figure 4.8. A Knowledge Visualization Pipeline

4.3.1.4 Wisdom Visualization (WV)

Besides data, information, and knowledge, the concept of wisdom visualization is also important in understanding the quality of visualized data. Most literatures do not consider the concept of wisdom due to the impossibility of achieving consensus and understanding its meaning (Scagnetti, 2009). As for Rowley (2007), he does not see the contribution of information and knowledge to wisdom. However, for Figueroa (2009), wisdom is all about the future that relies on knowledge and pattern models, giving an exponential competitive advantage. Wisdom comes from pure human skills with the combination of AI. The concepts of insight and intelligence is the metaphor for wisdom is to establish a visualization infrastructure can be an alternative approach to systematically collect, process, and analyze data. Using knowledge-based reasoning, knowledge can be inferred from cases of successes and failures,

common associations between datasets and control parameters, and other patterns exhibited by the systems, users, and interactions. Such knowledge may include a popular approach, commonly used parameter sets, the best practice, and an optimization strategy. Figure 4.9 shows the related infrastructure of wisdom visualization pipeline.

The general-purpose infrastructure can support multiple application domains. It can potentially enable applications to benefit from the best practice and software developed for other applications. The infrastructure can be developed based upon the advances in other areas of computing technologies, including semantic computing, autonomic computing, knowledge-based systems, data warehousing, machine learning, and search engine optimization.

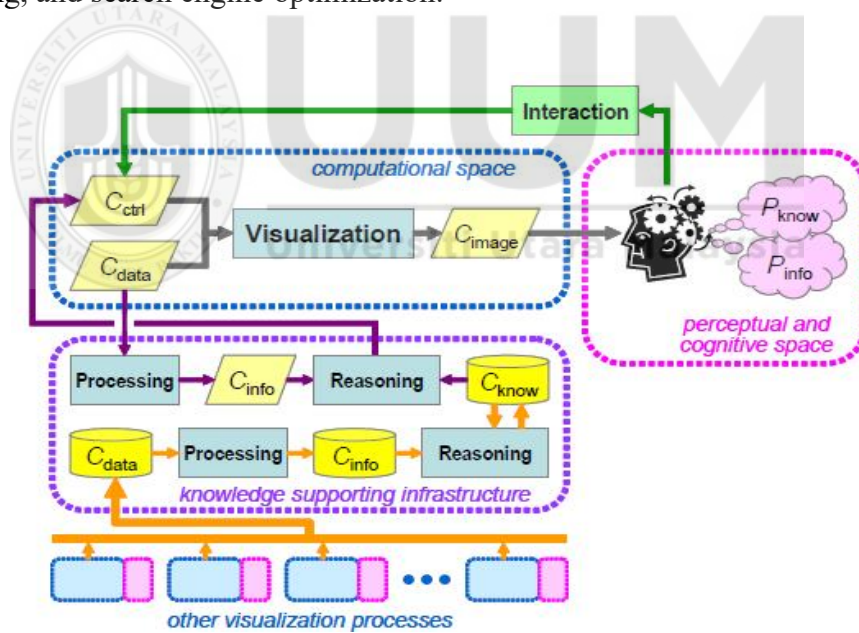


Figure 4.9. A Wisdom Visualization Pipeline

4.3.2 Analytic Components

Analytics uses mathematics, statistics, predictive modeling, and machine learning to find patterns in data. Big data analytics examines large amounts of data to uncover hidden patterns, correlations, and other insights. With today's technology, it is

possible to analyze large data and get answers from it almost immediately. A deeper analytic approach has been embedded to provide a visual platform for the analyst to interact with their data and models. Big data analytics helps organizations harness their data and use it to identify new opportunities. Three analytics approaches, descriptive, predictive, and prescriptive, have been introduced by Gartner (2012), which will help in the decision making process. Based on previous studies, only two approaches, descriptive and predictive analytics, were fully utilized and embedded in specific models (Gorg et al., 2013; Brown et al., 2012; Liu & Stasko, 2010; Jeong et al., 2009). Those that used the prescriptive analytics and tools are still scarce. Therefore, in this study, the integrated prescriptive analytics with interactive visualization were applied to support data exploration more effectively.

4.3.2.1 Descriptive Analytics

Descriptive, the simplest form of analytics, represents the first step in a complex process, which provides a solid foundation for further analytics. The objective of descriptive analytics is to answer the question of what rather than why this happened. The interesting fact about descriptive analytics refers to the powerful insights that can be obtained with some simple arithmetic operations, such as mean, median, mode, or minimum and maximum values.

In descriptive analytics, the Knowledge Discovery from Data (KDD) takes place to model data. KDD is defined as a method of finding, transforming, and refining meaningful data and patterns from a raw database (Fayyad, Haussler & Stolorz, 1996). This technique has evolved, and continues to evolve, from the intersection of research in various fields, such as databases, machine learning, pattern recognition, statistics, artificial intelligence, and reasoning with uncertainty, knowledge acquisition for expert systems, data visualization, and machine discovery.

In this study, descriptive analytics was used to determine the relationship between two variables; students' IUB and academic performance. Descriptive analysis was then performed to look at the frequency of Internet usage activities, amount of time spent on the Internet, most frequent Internet access points, Internet browsing goals, and most used Internet services. Mean, median, and mode were calculated to determine the most frequent IUB by students.

4.3.2.2 Predictive Analytics

Predictive analytics uses the findings from descriptive analytics to detect tendencies, clusters, exceptions, and future trends. This potential makes predictive analytics a valuable tool for forecasting. Despite numerous advantages, the accuracy of the prediction highly depends on the data quality and situation stability. Thus, the analytics requires careful treatment and continuous optimization.

When the descriptive analysis has successfully described IUB, the predictive analytics will then use the data to predict a student's performance. The results, generated in the form of algorithms and patterns, will formulate the model. Complex patterns or abstractions obtained from data mining procedures can be used in visualizations, for instance, to present the clustering or classification results. In addition, the automatically created model can be analyzed or visualized to derive insights. For example, logistic regression models learn weights of features, which can be used to identify most important features or feature combination.

4.3.2.3 Prescriptive Analytics

The purpose of prescriptive analytics is to literally prescribe what action to take to eliminate future problem or take full advantage of a promising trend. These analytics requires both historical data and external information due to the nature of statistical

algorithms. Besides, the use of advanced tools and technologies, such as machine learning, business rules, and algorithms, makes prescriptive analytics more sophisticated to implement and manage.

Most importantly, based on the predictive results, prescriptive analytics is able to provide recommendations. In this study, the human skills were embedded into the prescriptive analytics to offer recommendation based on the results visualized by dashboard. Prescriptive analytics will recommend by answering “how should you do”, which refers to the next action after the question “What is most likely to happen based on my current result, and what can I do to change that outcome?”

The prescriptive analytics in this study also formulated the recommendation action based on the predictive results. To achieve the prescriptive level, this study will apply clustering and classification technique. These techniques are important in prescriptive analytics because they help in understanding and categorizing data, identifying patterns, and making predictions or recommendations based on those patterns. Prescriptive analytics can be achieved with clustering and classification techniques by utilizing the insights gained from these techniques to guide decision-making and recommend optimal actions. By leveraging these techniques, prescriptive analytics can recommend personalized actions, optimize decision-making, and improve outcomes based on patterns and knowledge derived from the data.

These techniques enable the extraction of valuable insights from data, aid in decision-making, and enhance the effectiveness of prescriptive models in guiding optimal actions for desired outcomes. The outcomes has considered the weight age and the consequences action for every action taken by the decision-maker. The list of

recommendations and options resulted from the predictive analytics on the students' academic performance based on IUB.

4.3.3 Cognitive Approach

This study focused on the mixed-initiative visualization, in which both the computer and human initiated the processes and collaborated in the exploration and creation of knowledge. Both the human and computer bring strengths to the overall cognitive system. Complementary is one of the obvious strengths, is which further supports the potential of the collaboration. The cognitive approach, a logical extension of data analytics known as analytical learning driven by analytical models and hypotheses, is a next step for organizations to pursue. Ducharme and Angelelli (2014) suggest using cognitive as an advanced approach to capture and extract knowledge by elaborating the predictive analytics and cognitive computing.

4.3.3.1 Knowledge Data Driven (KDD) Process

The KDD (Knowledge Discovery in Databases) process is highly relevant to the development of PKV models as it provides a systematic framework for extracting knowledge and insights from data. PKV models aim to provide actionable recommendations or guidelines based on available data, and the KDD process helps in uncovering the underlying patterns, relationships, and trends in the data that can inform prescriptive modeling. Here's how the KDD process relates to the development of PKV models:

- (1) Data Understanding: The first step of the KDD process involves understanding the data, its structure, and the domain in which it operates. In the context of PKV, this step is crucial for identifying the relevant data sources, assessing data quality, and understanding the scope and limitations of the

available data. By understanding the data, it can determine its suitability for developing PKV models and identify any necessary data preprocessing steps.

(2) Data Preprocessing: Data preprocessing is a critical step in the KDD process that involves cleaning, transforming, and integrating the data to ensure its quality and consistency. For PKV model, this step helps in preparing the data for analysis, addressing missing values, handling outliers, and normalizing or standardizing the data. Data preprocessing ensures that the data used in the PKV model is reliable and suitable for generating meaningful insights and recommendations.

(3) Data Mining: Data mining is the core component of the KDD process, where patterns, relationships, and trends are discovered in the data. In the context of developing PKV models, data mining techniques can be applied to extract valuable knowledge from the data. This knowledge can include predictive models, descriptive patterns, and associations that can inform the recommendations provided by the PKV model.

(4) Knowledge Representation: After the data mining phase, the discovered patterns and relationships need to be represented in a form that is suitable for the development of the PKV model. This can involve transforming the mined knowledge into actionable rules, decision trees, or mathematical models that can guide the recommendations generated by the prescriptive model. The knowledge representation phase ensures that the extracted insights are effectively utilized in the development of the prescriptive model.

(5) Model Development: In the KDD process, model development involves constructing models based on the knowledge derived from the data mining phase.

For PKV model, this step entails creating the prescriptive model itself, which incorporates the discovered patterns and relationships to generate recommendations. The PKV model may utilize various techniques, such as machine learning algorithms, optimization methods, or rule-based systems, to provide actionable guidance.

(6) Evaluation and Deployment: The final steps of the KDD process involve evaluating the model's performance and deploying it in practical applications. In this study to develop the PKV models, evaluation ensures that the recommendations generated by the model are accurate, effective, and aligned with the desired outcomes. This step involves assessing the model's predictive accuracy, assessing the impact of recommendations, and conducting user feedback and validation. Once the PKV model is deemed reliable, it can be deployed for practical use.

By following the KDD process, this study can leverage data-driven insights to develop robust and reliable prescriptive models. By using the KDD process it can help in understanding the data, preprocessing it, mining knowledge, representing insights, and developing and evaluating the prescriptive model. This systematic approach ensures that the PKV models are built on a solid foundation of data analysis and knowledge extraction, enhancing their effectiveness in providing actionable recommendations.

4.3.3.2 Human Interaction

After conducting the visual analytics processes of the computer part, human interaction will take place to explore, verify, and generate knowledge. New visualizations or models are generated from the cognitive and reasoning elements.

The assumption that human interaction could fuse multisensory information in a reasoning process (Berniker and Kording, 2011) motivates the development of computational models to estimate the empirical input data (Samad et al., 2015). Accordingly, the cognitive and reasoning elements compute the predictive results (Samad et al., 2015) that proposed prescriptive solutions and recommendations based on the visual analytics outcomes. However, these estimations exhibit limited estimation accuracy (Samad et al., 2015). Hence, the rules of knowledge will take place whereby the knowledge from the expert (decision-maker) define these rules based on the decision-making process of a computational level. In the context of prescriptive analytics, the rules of knowledge play a crucial role. These rules are often defined by experts or decision-makers who possess domain expertise and understanding of the decision-making process. These rules are then incorporated into the computational models used for prescriptive analytics.

Once defined, these rules are incorporated into the computational models used for prescriptive analytics. The models utilize algorithms, machine learning techniques, or rule-based systems to process data, apply the decision-making rules, and generate recommendations or guidance. The rules serve as the guidelines or constraints that inform the model's output, ensuring that the recommendations align with the expert knowledge and desired outcomes.

In conclusion, incorporating the rules of knowledge based on the decision-making process of experts into computational models allows for the development of prescriptive analytics systems that align with expert knowledge and can provide valuable recommendations or guidance to decision-makers.

4.4 Summary

This chapter discussed the development of the model in this study. The discussion started by presenting an overview of previous related models; DIKW Model, Knowledge Generation Model, and Human Cognition Model. Several identified gaps were included in the proposed model of this study. Finally, the PKV model was developed based on the related model and theory. A prototype was developed based on proposed PKV model and explained in detail in chapter five.



CHAPTER FIVE

PROTOTYPE DEVELOPMENT

5.1 Introduction

This chapter described the prototype which serves as a proof of concept of the PKV model. The prototyping process validates the practicability and applicability of the proposed model. The proposed process model is used in developing the PKVS prototype. The prototype is ensured to comply with both the structural and content components of the proposed model.

5.2 Prototype Development

In verifying the PKV model as well as in achieving objective 3, a prototype was developed based on proposed PKV model. The prototype is named PKVS prototype. It was developed through three phases based on PKV model.

- i. Phase 1: Pre-Development PKV Prototype.
- ii. Phase 2: Development PKV Prototype
- iii. Phase 3: PKV Prototype Presentation.

Each phase of the PKV model was mentioned above are contain a set of sub-phases or components. The detail of each phase is described in the next section.

5.2.1 Phase 1: Pre-development PKVS Prototype

The objective of this stage is to conceptualize the design model for PKV. This pre-development phase contains two different stages: Domain analysis and dataset collection and data preparation for data cleaning and modelling.

5.2.1.1 Domain Analysis and Dataset Collection

This stage is to identify the need of the domain and the domain users so as to achieve a goal-oriented design. Also, for the development phase, the domain dataset is needed to help in the prototyping stage. Domain analysis is the process of understanding the domain where the knowledge visualization will be applied. It encompasses identifying the explicit knowledge needed to support the decision making process in the domain work activities (Lam et al., 2012).

In this study, data were collected and classified into two categories; students' demographic and internet usage between the year 2017 until 2019. The students' academic performance data were retrieved from the Academic Affair Department (HEA), which comprised of demographics information (matric number, gender, citizenship, semester, level of study, college and CGPA). The CGPA refers to the Cumulative Grade Point Average (CGPA), which represents a measurement for students' academic performance in that respective semester (Mayilvaganan & Kalpanadevi, 2014; Mueen et al., 2016). The details of data collection are shown in Table 5.1.

Table 5. 1.
List of Data Collection from Secondary Sources

No	Category	Feature	Dataset
1	Students' Academic Information	Matric Number	
		Name	
		Gender	1) Male 2) Female

	1) Malaysia
	2) Indonesia
	3) China
Citizen	4) Pakistan
	5) Nigeria
	6) Somalia
	7) Turki
	1) 172
Semester	2) 181
	3) 182
	4) 183
Level of Study	1) Undergraduate
	2) Postgraduate
	1) Bank Rakyat
	2) BSN
	3) Grantt
	4) MAS
	5) Maybank
	6) MISC
College	7) Petronas
	8) Proton
	9) Sime Darby
	10) TNB
	11) Tradewinds
	12) Others

Student Grade (CGPA)	Cumulative Point Average	Fail: 0.00 – 1.99
		Conditional Pass: 2.00-2.99
	Fail : C- to F	Pass: 3.00 – 3.32
	Conditional Pass: B- to C	Good: 3.33 – 3.66
	Pass: B	Very Good: 3.67 – 3.99
	Good: B+	Excellent: 4.00
	Very Good: A-	
	Excellent: A	

The students' internet usage data were collected and retrieved from the Universiti Utara Malaysia Information Technology Department (UUMIT) based on the activities on UUM_wifi. The students' internet activities can be detected through their matric number. The students' Access Log which records all their internet activities has been filtered into the following fields based on the analysis: (IP Address, Web Site URL, Date & Time, bandwidth (in and out), and the number of connections in a day). The internet browsing activity is categorized into 11 categories and the details are shown in Table 5.2. These influencing aspects are considered as input variables.

Table 5. 2.

The Attributes of Internet Usage for Predicting Student Performance

Variables	Description	Examples
X1- File System (FST)	File System is the system that controls how data is stored and retrieved.	CMD, NETBIOS-IP, NFS, PRINT-SRV, PRINTER, RCP, SUNRPC, SYSLOG, VF Cloud
X2- File Transfer (FTF)	File Transfer is a standard communication protocol used for the transfer of computer files from a server to a client on a computer network.	Aspera, Bigfile, BITS, Box, Candyfile, Dropbox, Enppy, FileNori, Foxy, FTP, FTP-DATA, FTPS, FTPS-DATA, HTTP DownloadManager, HTTP File Sharing, iCloud, iTunes
X3-Downloading (DWN)	Downloading is a method used to transmit a file from one computer system to another, usually smaller computer system.	QQ Download, RapidShare, WeDisk, TotoDisk, Yandex Disk
X4-Peer-to-Peer (P2P)	In Peer-to-Peer (P2P) networking, a group of computers are linked together with equal permissions and responsibilities for processing data.	eDonkey, ExoSee, FileTopia, Freenet, Furthur, Maze, Mercura, Mute, Napster, NNTP, Pando, POCO, QNext, RaySource, Real Link, RTMFP, Share, Shareman,
X5- Entertainment (ENT)	Entertainment is the platform that, given the attention and interest of a viewer, gives pleasure and delight to the viewer.	DailyMotion, Daum, Deezer, Divx WebPlayer, iKU, ImagoTV, iTunes, ITV, iView, JKStar, Joost, Kankan, Ku6, Netflix, Pandora, PodCast, PPFilm, Qiyi, QQ, Tudou, Xbox, Youku, Youtube,

X6-Web Browsing (WBS)	Web browsing is an application software related activity conducted for accessing the World Wide Web.	Akamai, AliceZone, Ameba, AppleCalendar, Baidu Web, BBC Sport, Bing, Colmex, Kankan Thunder Web, MbTrade, Yandex.
X7- Social Media (SCM)	Social media are an interactive technologies that allow the creation or sharing/ exchange of information, ideas, career interests, and other forms of expression.	AIM, AOL, Baidu, CamFrog, ChatOn, eBuddy, EyeBall, Facebook, ICQ, IM Plus, Joyn, Kakao, Libon Chat, MailRu, Messaging, Mxit, MySpaceIM, Telegram, Webex, WeChat, Whatsapp, Yahoo Chat.
X8-Learning (LNG)	Learning consists of an online website that provides an online class platform containing any kinds of education learning materials.	KhanAcademy, Coursera, W3Schools, TedEd, Codecademy, OpenCulture, OpenYale, AcademicEarth, Udemy, edX, Udacity, Lynda, FutureLearn,
X9-Online Gaming (OGM)	Online Gaming is a platform used for Streaming games from remote internet servers.	Armed Heroes, Ayakashi, Battlefield, Blizzard, CabalOnline, Call of Duty, CalshofClans,
X10-Online Shopping (OSH)	Online shopping is an online platform used for shopping activities by the user (e-shopping).	Amazon, eBay, amazonCo, rakuten, aliexpress, craigslist, taobao, Walmart,
X11-Email (EML)	Email is a platform that can send messages distributed by electronic means from one computer user to one or more recipients via a network.	AMOS Mail, Biff, CC-Mail, Gmail, Hotmail, IMAP, iNet, LOTUS-NOTES, MailRu, Ms Outlook, POP2, POP3, POP3 SSL, SMTP, Yahoo Mail.

5.2.1.2 Data Preparation: Data Cleaning and Modelling

This stage is to obtain a befitting data structure that addresses the domain needs, as observed in the previous stage. Since in this study is to achieve a more functional decision making support tool, it is expected that the currently obtainable structure of the data table would need cleaning, transformation and modelling. Also, researcher would model any missing data dimension or input missing values.

In data cleaning the researcher ensures all data dimensions are present in the dataset file or tables with logical connection. Data cleaning is important because it can improve data quality and increases overall productivity. This is compulsory according to interactive data visualization process methods.

In this study, two different analysis procedures and techniques were conducted to ensure that the collected data are suitable and clean before analyzing it by using SPSS. It includes applying missing data and removing outliers. When dealing with missing data, related data was deleted to reduce bias. The whole training data where one or several columns have null entries was deleted and proceed to the descriptive analysis. In SPSS, frequency distribution are run on each of the variables to see whether all data fall within the expected range with a Likert scale ranging from 1 – 5.

In summary, data preparation sets the stage for data analysis by transforming and organizing the data to make it suitable for analysis. Once the data is prepared, various techniques and methods can be employed to analyze and extract insights from the data, leading to meaningful interpretations, predictions, or recommendations. Next section will explain in details the data analysis part.

5.2.1.3 Data Analysis

Once the data has been prepared, it is ready for analysis. The specific steps and techniques used in data analysis can vary depending on the goals of the analysis and the nature of the data. At this stage, data analysis techniques include descriptive analysis, predictive analysis and prescriptive analysis and will explain the steps in next sub-section.

5.2.1.3.1 Descriptive Analysis

Descriptive analysis involves summarizing and describing the main characteristics of the data. This may include calculating measures of central tendency (mean, median, mode), measures of dispersion (standard deviation, range), and generating visualizations like histograms, bar charts, or pie charts. In descriptive analysis, data will go through the Knowledge Data Discovery (KDD) process.

a) Knowledge Data Discovery (KDD) Process

KDD is referred to as Knowledge Discovery in Database and is defined as a method of finding, transforming, and refining meaningful data and patterns from a raw database in order to be utilized in different domains or applications. There are 4 steps in KDD process in order to achieve the objectives to obtain descriptive results. In descriptive analytic, KDD process was done in 4 stages; data selection, data pre-processing, data transformation and data interpretation in order to get descriptive results.

1) Data Selection

After setting the goals and objectives, the data collected needs to be selected and segregated into meaningful sets based on availability, accessibility importance and quality. These parameters are critical for data mining because they make the base for it and will affect what kinds of data models are formed.

2) Data Pre-processing

In this research, the data cleaning was conducted to deal with noise reduction, errors detection and removal, and data inconsistencies for the purpose of improving the quality of data. Having completed the first step, data analysis and cleaning, the 969 data are ready to be transformed. Once transferred to the excel sheet, the data are ready for the transformation activity. The file was then transformed into the arff format that represents the standard format required by the WEKA Data Mining toolkit which was used in building the model (Nasr et al., 2019). WEKA version 3.6.4 was used for the experimentation purposes in this research, which contains several tasks such as pre-processing, clustering, classification, association (correlation and regression) and visualization.

3) Data Transformation

In the context of the Knowledge Discovery in Databases (KDD) process, data transformation is a key step that involves converting the raw data into a format suitable for further analysis and mining. This step prepares the data to be fed to the data mining algorithms. Hence, the data needs to be in consolidated and aggregate forms.

In this study, data is transformed to represent it in a standardized or normalized format, making it suitable for analysis. The data is consolidated on the basis of functions, attributes, features etc. In this step, data was transformed into excel format and arff file to convert into WEKA tools. Data was grouped together or summarizing data at higher levels of granularity by using aggregation techniques involve computing statistics such as sum, average, count, or maximum/minimum values for subsets of data.

4) Data Interpretation

Frequencies are present in percentages and cumulative percentages. It is shown in the form of a bar chart, histogram or pie chart to identify data patterns. It describes as the most common phenomenon in the data. Descriptive analysis is divided into 2 parts, namely the background of the respondents and the internet usage pattern among students. The following is the profile of respondents by percentage and frequency and followed by level of WiFi usage by rate and percentage of users.

Throughout the procedure, 21% was incomplete data. Once cleaned, a set of 987 respondents or 78% of the data were found suitable for further analysis (Table 5.3).

With this final set of data, analyses were executed.

Table 5. 3.
Demography of the respondents

Student Background	Frequency	Percentage
Student Citizen		
Malaysia	907	62.62
International	80	37.38
Current Education Status		
Bachelor	920	68.69
Master	30	14.02
PhD	37	17.29

5.2.1.3.2 Predictive Analysis

To achieve the objective of predicting student performance based on internet usage activities, in predictive analysis, three main Data Mining are involving which are clustering, classification, and correlation are the best techniques to be used starting from raw data processing to knowledge extracting.

a) Data Mining

Data mining is as much analytical process as it is specific algorithms and models. To achieve the objective of prescribing the best model of internet usage and its impact on students' performance of this study, the DM, which involve clustering, classification, correlation, and regression analysis, are the best techniques to be used starting from raw data processing to knowledge extracting.

Data mining techniques such as clustering, classification, correlation, and regression analysis are commonly used in the process of knowledge extraction from raw data

due to their effectiveness in uncovering patterns, relationships, and insights. These techniques are considered effective to use in this study because they enable the discovery of patterns, dependencies, and relationships within the data, leading to actionable insights and knowledge extraction. They provide a structured and systematic approach to analyzing complex datasets, making predictions, understanding data distributions, and extracting valuable information that can support decision-making processes.

b) Clustering

After the required data has been collected and processed, the clustering technique was performed to group the data into different cluster. Clustering technique helps categorize objects within the data by identifying similarities and differences between them. This is a useful technique to identify patterns in data for further analysis and interpretation. It looks for and analyzes patterns in data samples before categorizing them. Thus, it can reduce the dimensionality which is the number of attributes of datasets by grouping similar items together. Furthermore, it helps simplify the process and improves the efficiency of the analysis.

In this study, the clustering performance was evaluated in terms of the three widely used criteria; execution time, purity, and NMI. The value must be within 0 and 1. Table 5.4 shows the total number of execution time when simple k-Means, CobWeb, Hierarchical, and EM algorithms were applied.

Table 5.4.
Execution Time of Different Clustering Techniques

Clustering Algorithm	Execution Time in second
k-Means	0.03
CobWeb	1.61
Hierarchical	3.06
EM	29.89

From the comparison, EM was identified as the best clustering technique with distribution purity of 0.593 and NMI of 0.048 as compared to the Hierarchical, k-Means, and Cobweb. However, the algorithm takes more execution time. The other clustering algorithms obtained much worse purity values (50% - 20%) than EM. This finding indicates that the EM algorithm performs well compared to the other three clustering algorithms, which is in line with the previous study conducted by Kostopoulos et. al (2015). In this study, the students' performance was evaluated using the EM algorithm.

c) Results

Having done the clustering evaluation, the decision on the best algorithm to evaluate the students was made by employing the EM technique for further statistical analysis. The algorithm was applied to determine the averages of the internet usage categories attributes. The EM algorithm is a widely used method that is applicable for clustering data based on quantitative variables and has been used to discover the underlying patterns concept of the dataset (Singh et al.,2016). The total number of clusters is

four (excellent, pass, good, and fail) as suggested by Asdaque et. al (2010) under students' performance. Table 5.5 lists the mean and standard deviation of the clusters produced by the EM method.

Table 5.5.
Clustering Results of Internet Usage

IUB	Mean / Std Deviation	0	1	2	3
X1	Mean	44.63	29.34	49.07	37.18
	Std Deviation	49.51	22.63	53.32	42.69
X2	Mean	22.77	7.08	13.56	7.03
	Std Deviation	43.74	13.39	25.95	12.60
X3	Mean	12.71	4.51	17.18	7.03
	Std Deviation	18.63	8.29	36.50	12.66
X4	Mean	2.09	0.98	8.03	21.53
	Std Deviation	3.30	2.17	30.64	66.28
X5	Mean	4.99	1.60	7.15	1.14
	Std Deviation	7.63	2.63	14.41	1.59
X6	Mean	33.40	33.41	31.57	45.51
	Std Deviation	30.07	30.06	36.71	60.65
X7	Mean	14.60	14.59	6.03	4.25

	Std Deviation	22.44	22.44	7.41	6.71
	Mean	0.93	0.93	0.00	0.00
X8	Std Deviation	3.48	3.47	0.00	0.00
	Mean	0.87	0.87	0.01	0.08
X9	Std Deviation	1.74	1.74	0.02	0.24
	Mean	0.01	0.01	0.49	0.02
X10	Std Deviation	0.02	0.02	0.21	0.04
	Mean	3.96	3.96	0.06	0.11
X11	Std Deviation	10.57	10.57	0.19	0.36

The results in Table 5.5 portray that the X1 (File System) is at the top rank of the internet usage categories which has been browsed by cluster 2. X6 (Web Browsing) is the second highest which has been browsed by cluster 3 and the third is X2 (File Transfer) under cluster 0. From the results, there are differences between the percentages of the internet usage activities that have been used by different clusters. Therefore, it can be concluded that different clusters have various internet usage activities.

d) Classification

In this study, eight different classification methods were applied to classify the data. The performance of the classification methods produced by the Support Vector Machines (SVM), Part (PRT), Decision Tree (DT), Random Forest (RF), Neural

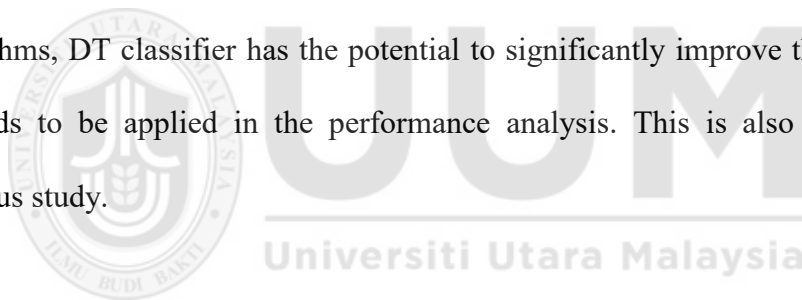
Network (NN), AdaBoost (ADB), Naïve Bayes (NB), K Nearest Neighbor (KNN) was then compared. The accuracy of the predictive model is calculated based on the accuracy, precision, recall, F-measure, kappa and time to build a model for the classification. Results start from 0 to 100. The greater the value, the high accuracy of the algorithms. The results of the experiments are shown in Table 5.6.

Table 5.6.
Performance of the Classifiers

Classifiers	N1	N2	N3	N4	N5	N6
DT(J48)	0.949	0.952	0.950	0.949	0.941	0.050
PRT	0.943	0.945	0.943	0.942	0.943	0.050
RF	0.887	0.905	0.887	0.876	0.867	0.110
NN	0.855	0.857	0.855	0.833	0.830	0.130
SVM	0.824	0.834	0.824	0.823	0.794	0.160
KNN	0.717	0.732	0.717	0.707	0.669	0.060
NB	0.389	0.385	0.390	0.350	0.282	0.090
ADB	0.352	0.352	0.352	0.350	0.216	0.030
N1 : Accuracy N2 : Precision N3: Recall N4: F-Measure N5:Kappa N6:Time to build model						

Table 5.6 presents the comparison of the eight different classifiers results. The comparison shows that J48 and PRT have the highest accuracy of 94.9% and 94.3%, respectively. This indicates that DT has the best performance compared to the other classifiers. The other algorithm yields an average accuracy of 80% and the two

lowest accuracy scores are those of Naïve Bayes (38.9%) and AdaBoost (35.2%) classifiers. In this experiment, the under-tree learner requires the shortest time to build the model which is around 0.05 to 0.11 seconds compared to the others. DT and RF are categorized under the trees learner. However, based on this experiment, DT offers the perfect performance in terms of accuracy and time to build the model as compared to the RF. In DT, the training period is also less than that of the RF because it generates only one tree unlike forest of trees in the RF. This shows that the DT is a more easily comprehensible model since the algorithm is simple to understand, interpret, and visualize as the idea is mostly used in our daily lives. Output of a DT can be easily interpreted by humans because it supports the human reasoning process. These results suggest that among the tested machine learning algorithms, DT classifier has the potential to significantly improve the classification methods to be applied in the performance analysis. This is also evidenced in a previous study.



e) Validation on the Classification Model

Once we are done with training the model, we just can't assume that it is going to work well on data that it has not seen before. We need some kind of assurance of the accuracy of the predictions that our model is putting out. For this, we need to validate our model. This process of deciding whether the numerical results quantifying hypothesized relationships between variables, are acceptable as descriptions of the data, is known as validation.

In this approach we randomly split the complete data into training and test sets. Then perform the model training on the training set and use the test set for validation purpose, ideally split the data into 90:10, 80:20, 70:30, 60:40, 50:50, 40:60, 30:70,

20:80 and 10:90. With this approach there is a possibility of high bias if we have limited data, because we would miss some information about the data which we have not used for training (Yafooz et al., 2020). If our data is huge and our test sample and train sample has the same distribution, then this approach is acceptable. The results of these cross validation of classification models on some of the colossal datasets are shown below in Table 5.7.

Table 5.7.
Cross Validation on the Classification Models

k-fold	Accuracy	Time taken to build the model
90 : 10	97.87%	0.17
80 : 20	97.87%	0.02
70 : 30	97.87%	0
60 : 40	97.66%	0.02
50 : 50	97.87%	0.01
40 : 60	97.87%	0.01
30 : 70	97.66%	0
20 : 80	97.66%	0
10 : 90	97.66%	0

After analyzing the usage of k-fold cross-validation for J48 classification model, from the result in Table 5.7, we can see that the highest percentage is 97.87% from the nine results k-fold test. However, based on, Yadav and Shukla (2016), indicating that we can indeed go for 40:60 k-fold cross-validation over other k-fold validation on colossal datasets for quality classification even though it gives the same results. It

indicates that however training data is small representing for 40 % over 60% for testing data, but the results are greater than the others. So, for the J48 algorithm, the results show that 40:60 through the k-fold cross validation is better than the other k-folds. Therefore, among the machine learning algorithms tested, J48 classifier has significantly improve the conventional classification methods to be used in EDM. In addition, the performance of the J48 stamps was at its superiority based on the accuracy and shortest model development time. This led to the use of the DT algorithm in this study to evaluate students' performance. The DT classification (J48) combined with the clustering algorithm (EM) under 40:60 k-folds were tested by using the required dataset.

f) Results

The comparison between the previous lead to the used of the best classification algorithm to predict the students' performance. Thus, such algorithm is very useful in detecting students that are likely to fail, so that early prevention can be adapted to solve the problem. The DT classification algorithm models (J48) are described together with the clustering algorithm (EM) obtained from the dataset that gave the highest accuracy value. The results are depicted in Table 5.8, while the pruned tree performed by J48 and set of rules are included in Figure 5.1 and Figure 5.2, accordingly.

Table 5. 8.
Detailed Accuracy by Class

	TP Rate	FP Rate	Precision	Recall	F-Measure
	1.000	0.000	1.000	1.000	1.000
	1.000	0.000	1.000	1.000	1.000
	0.987	0.008	0.963	0.987	0.975
	0.990	0.000	1.000	0.990	0.995
	0.962	0.003	0.987	0.962	0.974
	1.000	0.002	0.950	1.000	0.974
	1.000	0.000	1.000	1.000	1.000
	0.987	0.003	0.987	0.987	0.987
	1.000	0.000	1.000	1.000	1.000
Weighted Avg.	0.987	0.002	0.987	0.987	0.987

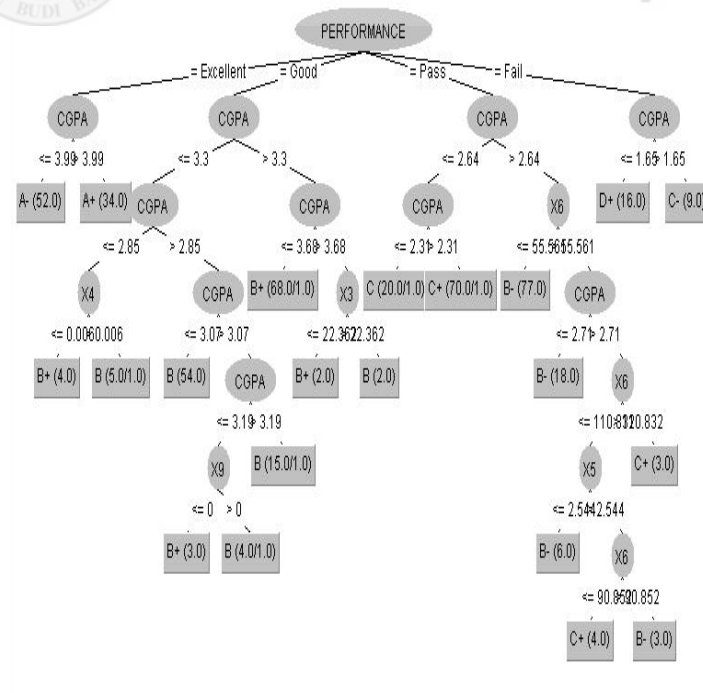


Figure 5.1. The Decision Tree generated from the J48 Algorithm to Predict Students' Performance

J48 pruned tree

PERFORMANCE = Excellent

| CGPA <= 3.99: A- (52.0)

| CGPA > 3.99: A+ (34.0)

PERFORMANCE = Good

| CGPA <= 3.3

| | CGPA <= 2.85

| | | X4 <= 0.006: B+ (4.0)

| | | X4 > 0.006: B (5.0/1.0)

| | CGPA > 2.85

| | | CGPA <= 3.07: B (54.0)

| | | CGPA > 3.07

| | | | CGPA <= 3.19

| | | | X9 <= 0: B+ (3.0)

| | | | X9 > 0: B (4.0/1.0)

| | | CGPA > 3.19: B (15.0/1.0)

| CGPA > 3.3

| | CGPA <= 3.68: B+ (68.0/1.0)

| | CGPA > 3.68

| | | X3 <= 22.362: B+ (2.0)

| | | X3 > 22.362: B (2.0)

PERFORMANCE = Pass

| CGPA <= 2.64

| | CGPA <= 2.31: C (20.0/1.0)

| | CGPA > 2.31: C+ (70.0/1.0)

| CGPA > 2.64

| | X6 <= 55.561: B- (77.0)

| | X6 > 55.561

| | | CGPA <= 2.71: B- (18.0)

| | | CGPA > 2.71

| | | | X6 <= 110.832

| | | | X5 <= 2.544: B- (6.0)

| | | | X5 > 2.544

| | | | | X6 <= 90.852: C+ (4.0)

| | | | | X6 > 90.852: B- (3.0)

| | | X6 > 110.832: C+ (3.0)

PERFORMANCE = Fail

| CGPA <= 1.65: D+ (16.0)

| CGPA > 1.65: C- (9.0)

Number of Leaves : 21

Size of the tree : 39

Time taken to build model: 0.02 seconds

Figure 5.2. The Code Generated from using the J48 Algorithm to Predict Students' Performance

Based on Table 5.8, further evaluation was performed with the best classifiers accuracy once the classification analysis and comparison were made. The comparison among the eight algorithms signifies that J48 has the highest accuracy, whilst the EM

g) Correlation

The Pearson's Correlation Coefficient (PCC) was employed for measuring the degree of the relationship between students' performance and students' internet usage. The results in Table 5.9.

Table 5. 9.
Correlation Coefficient of Student Performance and IUB

Correlations													
		CGP A	X 1	X2	X 3	X4	X 5	X6	X 7	X8	X9	X 10	X1 1
C G P A	Pearson	1	.0	-	.0	-	.0	-	.0	-	-	.0	.00
	Correlation		6	.05	16	.02	15	.03	12	.01	.118	45	0
			6	6		2		5		7	*		
	Sig. (2-tailed)		.153	.227	.731	.644	.752	.444	.788	.718	.012	.334	.996
N		469	469	469	469	465	469	469	468	452	457	464	464
*. Correlation is significant at the 0.05 level (2-tailed).													
**. Correlation is significant at the 0.01 level (2-tailed).													

From the Table 5.9 shows the analysis results of the correlations between CGPA and 11 internet usage categories. It can be concluded that there is a significant correlation between X9 (Online Gaming) and student performance when $p = 0.012$. The negative correlation of $r = -0.118$ indicates that if the online gaming is high; the students' CGPA decreases. However, the correlation coefficient of the whole internet usage activities is weakly significant.

Based on the Data Mining technique by leveraging clustering, classification, correlation, and regression, organizations can make data-driven decisions, anticipate trends, and optimize strategies based on the predictive models' outputs. These techniques in predictive analytics provide valuable insights into patterns, relationships, and dependencies within the data, enabling accurate predictions of future outcomes. Next section will explain the technique to provide the actionable recommendations by using prescriptive analysis.

5.2.1.3.3 Prescriptive Analysis

To achieve the objectives to prescribe the recommendations based on students' internet usage activities, prescriptive analysis was conducted by using regression techniques.

a) Regression

Each of the predictive models was evaluated using the following R Square criteria, which represents the percentage that a model can explain its output based on a training dataset. The higher the R-square value, the better is the model. In this study, the forecast model for the students' performance was tested and predicted against their internet usage.

The multiple regression equation explained above takes the following form:

$$y = b_1x_1 + b_2x_2 + \dots + b_nx_n + c$$

a) Student Performance (Fail)

$$\begin{aligned} SP(\text{Fail}) = & 1.506 + (0.003*X_1) + (0.0000*X_2) + (0.000*X_3) + (-0.065 *X_4) \\ & + (0.003*X_5) + (-0.004*X_6) + (-0.003*X_7) + (0.000*X_8) + (0.051* X_9) + \\ & (0.008*X_{10}) + (0.247*X_{11}) \end{aligned}$$

Table 5. 10.

Model Summary of the SP(Fail) Regression

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.920 ^a	.846	.653	.18301
a. Predictors: (Constant), EML, P2P, DWN, OGM, FTF, FST, ENT, SCM, WBS, OSH				

The Table 5.10 shows the results of the regression model for students who failed in their exam. Based on the regression results it shows a high correlation between CGPA and internet usage based on the R = 0.920 and R Square of 0.846. This indicates that the models predict student performance as fail is highly predicted.

b) Student Performance (Pass)

$$\begin{aligned} SP(\text{Conditional Pass}) = & 2.477 + (0.001*X_1) + (4.723*X_2) + (0.001*X_3) + \\ & (0.000*X_4) + (-0.001*X_5) + (0.000*X_6) + (-0.001*X_7) + (-0.007*X_8) + (-0.013*X_9) \\ & + -0.051*X_{10}) + (0.001*X_{11}) \end{aligned}$$

Table 5.11.

Model Summary of the SP(Pass) Regression

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.289 ^a	.084	.013	.22850
a. Predictors: (Constant), EML, WBS, DWN, OGM, ENT, SCM, LNG, P2P, OSH, FTF, FST				

The Table 5.11 shows the results of the regression model for students who passed their exam. Based on the regression results it shows weak correlation between CGPA and internet usage based on the R = 0.289 and R Square of 0.084. This indicates that the models for student performance that have passed are weakly correlate.

c) Student Performance (Good)

$$\text{SP(Good)} = 3.274 + (8.494 \cdot X_1) + (-0.001 \cdot X_2) + (0.000 \cdot X_3) + (0.000 \cdot X_4) + (0.006 \cdot X_5) + (-0.001 \cdot X_6) + (0.000 \cdot X_7) + (0.007 \cdot X_8) + (-0.097 \cdot X_9) + (0.027 \cdot X_{10}) + (-0.002 \cdot X_{11})$$

Table 5. 12.

Model Summary of the SP(Good) Regression

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.391 ^a	.153	.068	.21040
a. Predictors: (Constant), EML, LNG, ENT, OGM, OSH, FTF, DWN, P2P, FST, SCM, WBS				

The Table 5.12 shows the results of the regression model for students who performed well in their exam. Based on the regression results it show weak correlation between CGPA and internet usage based on the $R = 0.391$ and R Square of 0.153. The models predict student performance as good is weakly correlate with the internet usage.

5.2.2 Phase 2: Development

The objective of this phase is to actualize the PKV conceptualized from the previous phase. This aim for exploration and visualization of students' internet data to support the IHL decision making. To achieve this, four different stages are accomplished: PKV component development, core content development, PKV features integration and heuristic evaluation.

5.2.2.1 PKV Component Development

The objective of this stage is to design the prototype, starting with a low-fidelity form, especially of its visual interactive interface (front-end). This can be done with paper sketching. The PKV content development deals with the process of the developing content delivery techniques using the suitable programming language frameworks. This must be done to support related perceptual, cognitive and decision supports with respective theoretical considerations. The development of system components involves requirement analysis and design stage.

a) Requirement Analysis

This stage involves understanding the requirements and specifications of the system, as well as identifying the functionalities and services that need to be implemented as individual components. It includes gathering requirements from stakeholders, analyzing user needs, and determining the scope of the component development. At

this stage, to achieve the objectives to support the decision making process through the use of visualization, research has been done on the visualization technique that can be used to design the prototype. The selection criteria include relevance to the data, organization goals, quality and technical constraints such as limits on data volume and data types. Next the design will take place after the requirement analysis.

b) Design

The design phase involves creating a blueprint or plan for the system components. It includes architectural design, interface design, and detailed design of each component. The design should consider factors such as modularity, reusability, scalability, and interoperability with other system components. At this stage, the design part will focus on the usability and support the user cognition by using the visualization.

5.2.2.2 Core Content Development

The objective of the stage is to implement the software development technologies so as to bring the conceptualized design and low fidelity prototype into real state. This stage involves the core technical aspect of PKV development. At this stage, the front-end design with much attention to the theoretical suggestion for visualization interface design to aid perception, cognition and decision making (Teets Tegarden & Russell, 2010). In this stage, the actual coding and development of the system components take place. Developers write the necessary code, following the design specifications and best coding practices. This may involve programming in various languages, using appropriate frameworks or libraries, and integrating with other

existing components or systems. In this study, the system used powerBI since this software support the visualization.

5.2.2.3 PKV Features Integration

This stage is to perfect the prototyping process by bringing the PKV characteristics into reality. By using body structure and any element of visualization tools for creating data visualization. At this stage, the core element of KV features, overview, filter, demand details and zooming as earlier listed is integrated and their working perfected. System components undergo rigorous testing to ensure they function as intended and meet the specified requirements. This includes unit testing, integration testing, performance testing, and validation against expected outputs. Quality assurance processes ensure the components adhere to coding standards, are bug-free, and perform as expected.

5.2.3 Phase 3: PKV Prototype Presentation

This stage, the PKVS prototype presented to the end user. During this stage, the respondent had to explore and use the PKVS prototype. After they complete the task, the heuristic evaluation which is the users' experience evaluation experiment is conducted. In this study, usability testing for this PKVS prototype was conducted for usability experts. Usability testing is one of the important quality characteristics of software systems and products (Wirasasmia, & Uska, 2019). The usability testing was done through the experts' interaction with the prototype using their heuristic experience (Tory & Moller, 2005). The experts were the domain users; practitioners that using this prototype such as system administrator and the second is policy maker/decision maker in IHL such as dean of every school in IHL.

5.3 Screenshots of PKV Prototype

The following screenshots in Figure 5.3 to Figure 5.7 are the user interfaces of PKV prototype. When the web-based system is accessed, the landing page shows the whole of the system. The best thing about this system, only one page contains the whole information about the results. The system applied visualization techniques which are Geo Chart like Map view and motion chart that contains bar chart and pie chart.

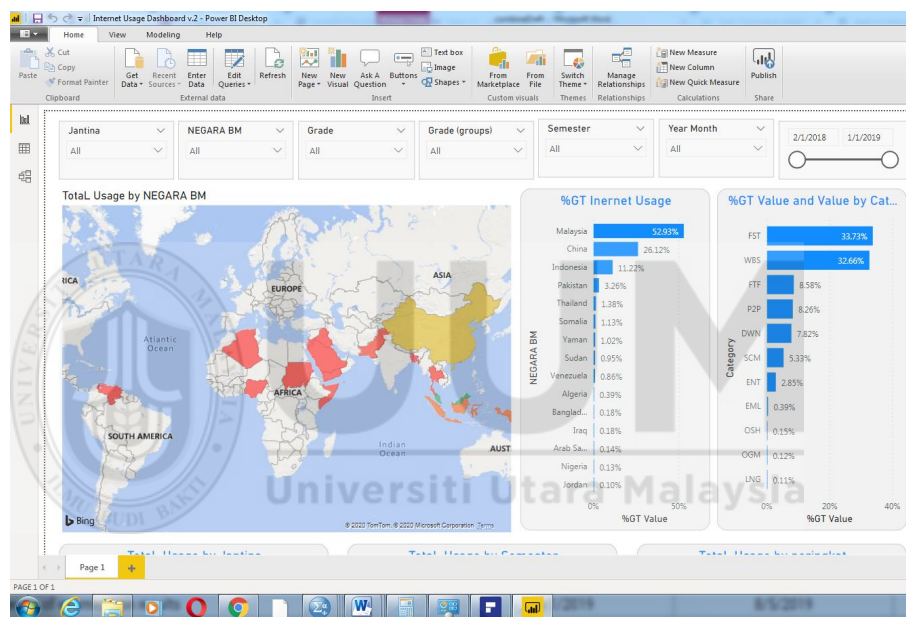


Figure 5.3. Top Page of PKV Prototype

On top of the web is the Geo Chart. Since this embedded with the visualization, then the whole system contains full of colors that can attract viewers. User can click on geo chart and the results will appear automatically. Geo chart gives a population distribution of the students' Internet usage based on their nationalities. On the right side of the system is the graph of Internet usage percentage and the internet category. In this study, the system automatically distinguishes and separate the internet categories based on 11 categories.

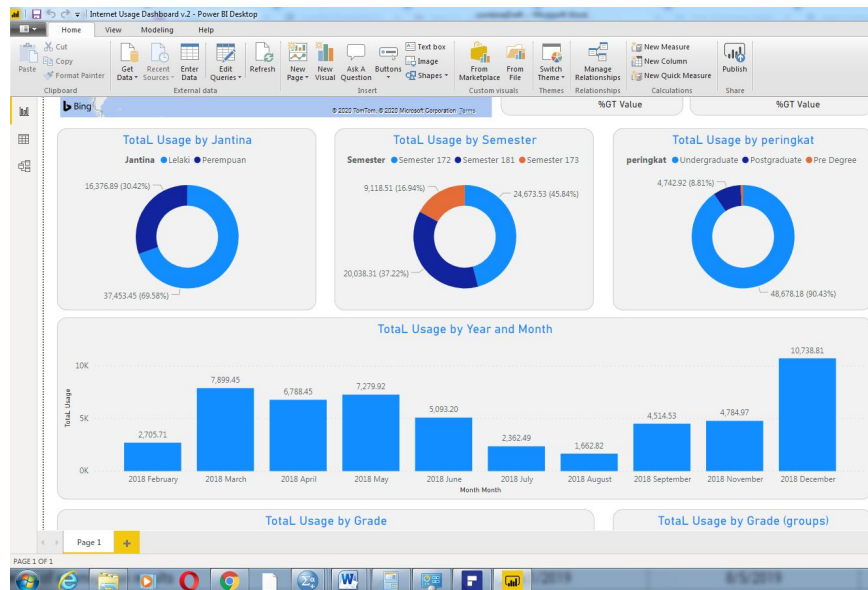


Figure 5.4. Second Layers of PKV Prototype

Scrolling as a distortion technique is used in accessing full information about the data. In Figure 5.4, users can scroll and see the second part of the web. It contains pie chart that inform percentage of gender, semester of students and level of study. On the bottom part, there is a graph showing the total usage of the internet usage by month and year.

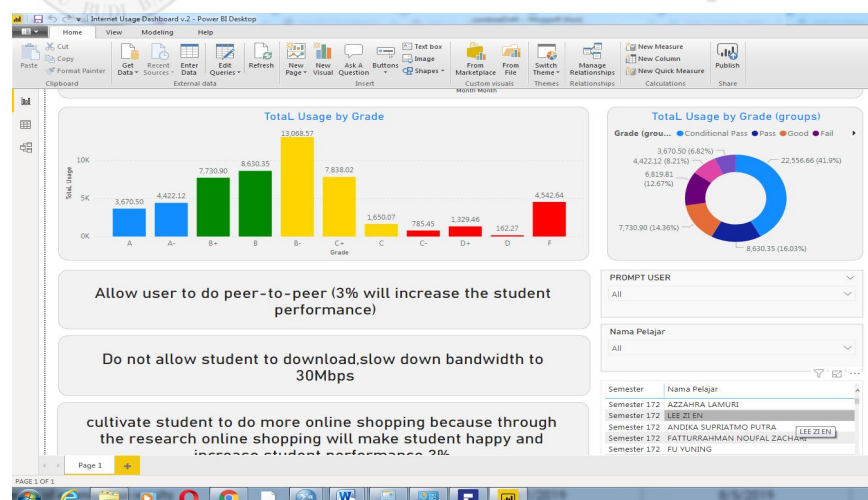


Figure 5.5. Third Layers of PKV Prototype

The Figure 5.5, third layer contains the students' total usage by grade. 11 students' grade is generalized on students' CGPA. This 11 students' grade categorized based university assessment in Malaysia. Below the students' total usage by grade is the

recommendations that propose to decision maker based on the grade. The system will list down the top three recommendations was formularized by the system itself through prescriptive analytic along with the weighted percentage to recommend to the user. This recommendation suggested by knowledge base and already validated through expert review method.

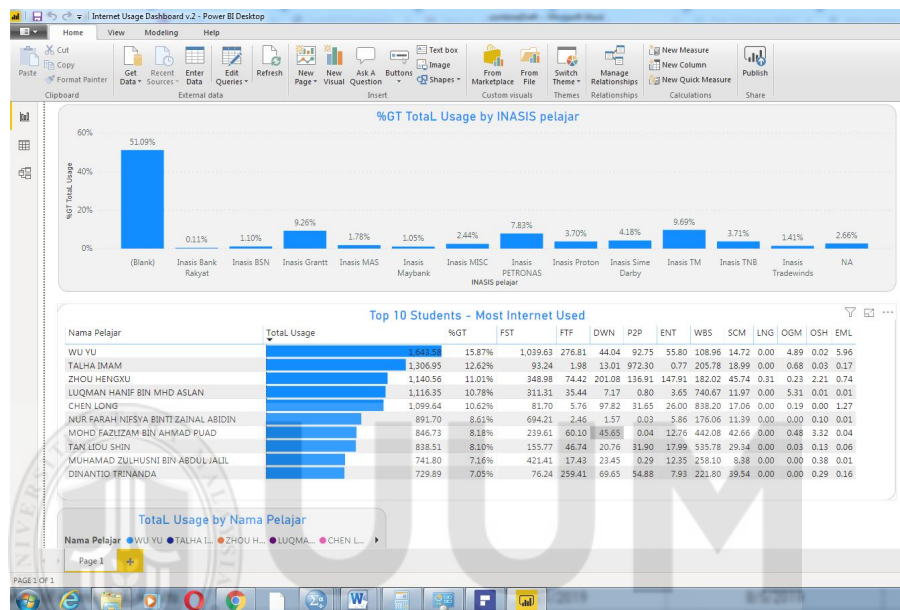


Figure 5.6. Fourth Layers of PKV Prototype

In fourth layer of PKV system in Figure 5.6, the students' Internet total usage group by their inasis (college) is presenting. From there, decision maker will know which inasis that used internet frequently.

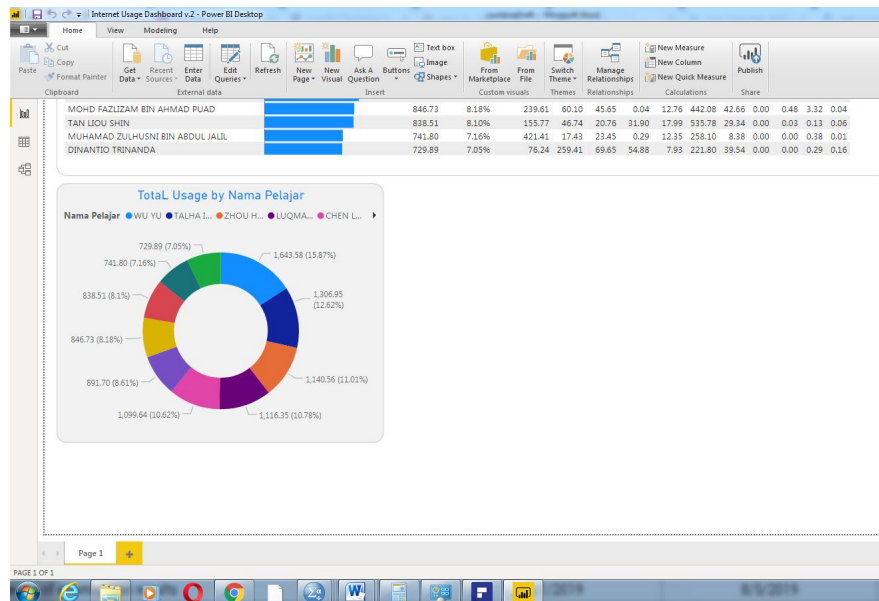


Figure 5.7. The Bottom page of PKV Prototype

Through data exploration, the usual cognitive load caused by multidimensionality of the students' data is reduced because the user can pick the dimensions of interest. This follows the cognitive load theory based on Sweller's. The different colors are used for the representation of the entities and the reaction to dynamic hinting support process visualization theory. For summary, all the prototype is built according to the respective theories and applicable in the development of the PKV prototype.

5.3.1 Descriptive Analysis

The following screen shots (Figure 5.8 to 5.13) depict the descriptive analysis from the student performance based on IUB. Visualizations like bar charts, pie charts, or line graphs used to present these summary statistics.



Figure 5.8. The Student Demographic Based on the Country.

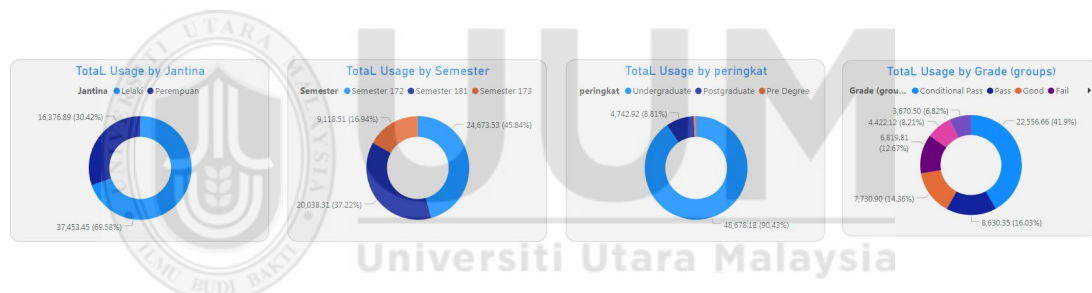


Figure 5.9. The Student Demographic Based on the Gender, Semester, Level of Study, and Grade.

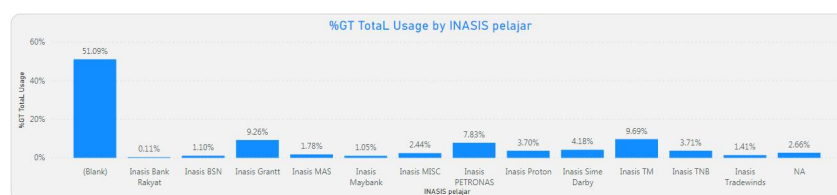


Figure 5.10. The Student Demographic Based On The College (Inasis)

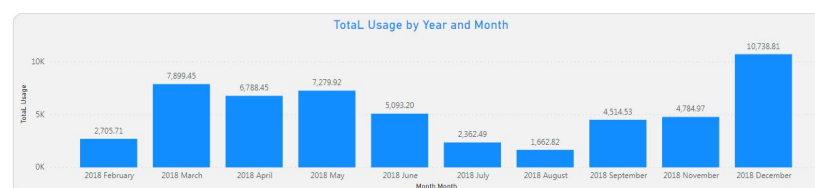


Figure 5.11. The Descriptive Analysis of IUB Based Year and Month.

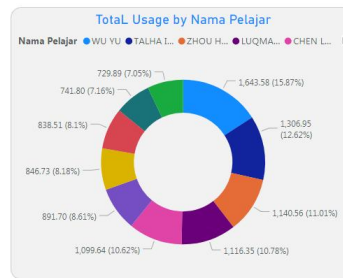


Figure 5.12. The Descriptive Analysis of IUB Based on Students Name.

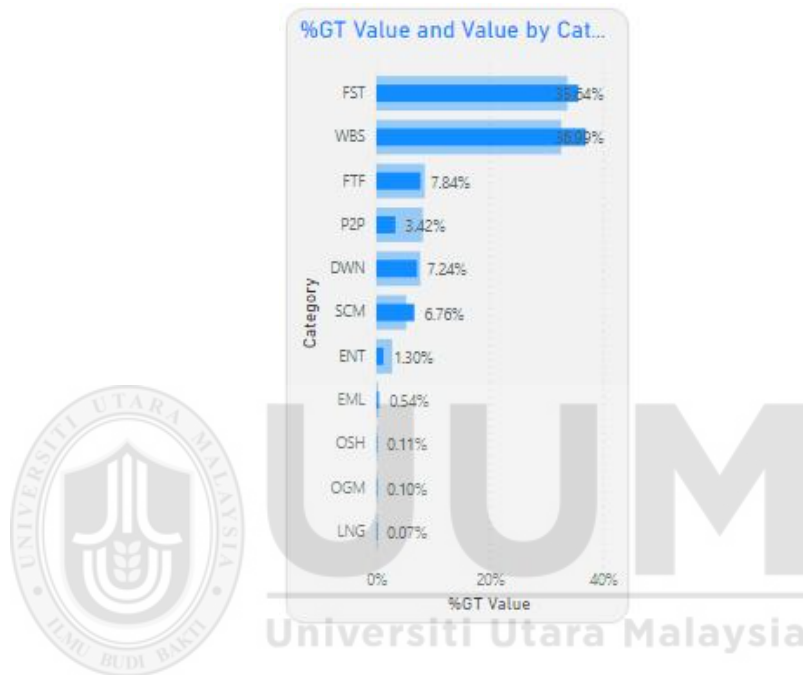


Figure 5.13. The Total of IUB Based on IUB Category.

For the descriptive analytic, from the dataset that includes various variables such as student demographics based on country, gender, semester, level of study, grade and college(inasis), and IUB analysis based on month and year, total usage of IUB and the total of usage based on IUB category. The dashboard provide an overview of key performance indicators. Next subsection explain on the predictive analysis.

5.3.2 Predictive Analysis

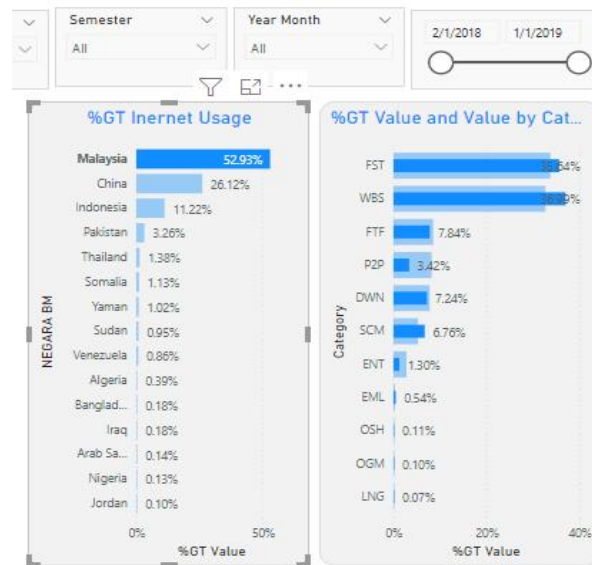


Figure 5.14. The Predictive Analysis of PKV Prototype.

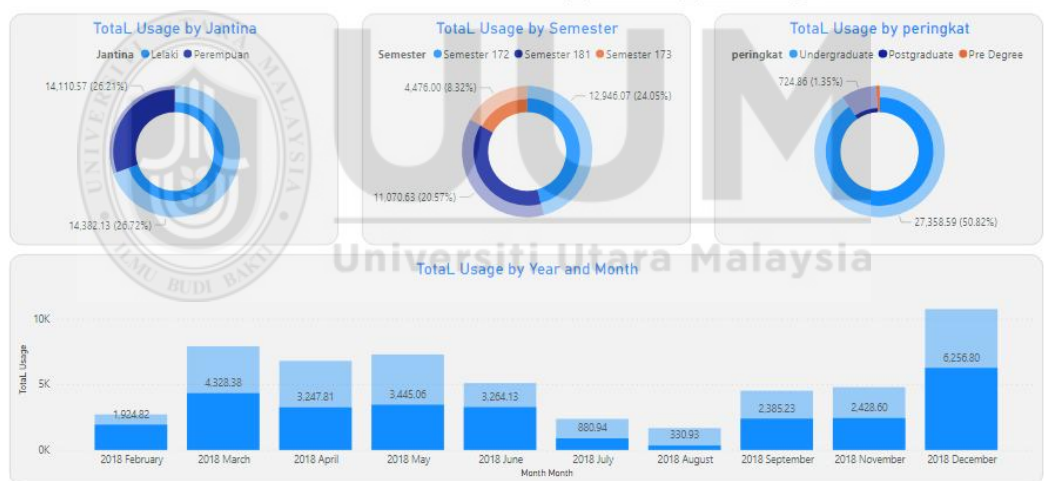


Figure 5.15. The Predictive Analysis of PKV Prototype.

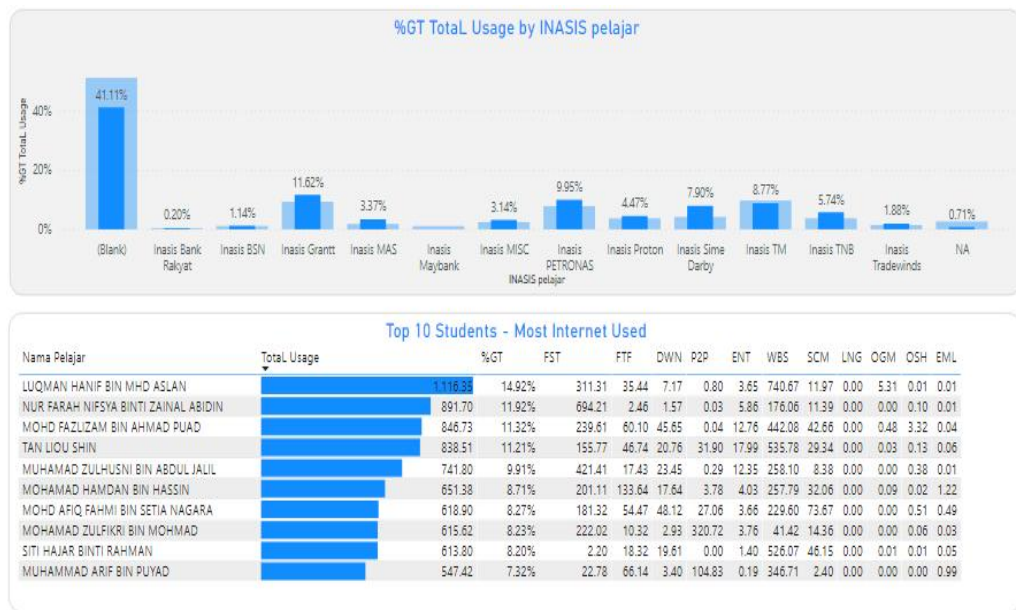


Figure 5.16. The Predictive Analysis of PKV Prototype.

In Figure 5.14 to Figure 5.16 visualized the predictive analysis page. The results presenting in the form of graph. Based on the descriptive analysis on student demographics, students grades as a measurement student performance link with their IUB category in the IHL. The internet usage pattern relate with students' CGPA are mapped into this system. When the system clicked at certain figure, it will automatically visualize the result through the process of predictive analytic. Here's how predictive analysis could be applied to identifying at-risk students: By leveraging predictive analytics, a model could be built to identify students who may be at risk in academic. Factors such as low high school grades based on the IUB activities will predict the students' grade. Early identification of at-risk students could enable the implementation of targeted interventions and support programs.

5.3.3 Prescriptive Analysis

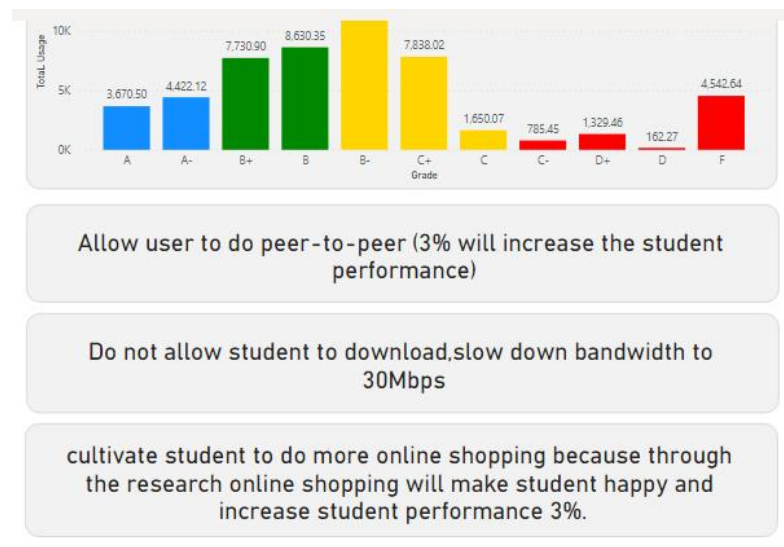


Figure 5.17. The Prescriptive Analysis of PKV Prototype

In Figure 5.17 is the prescriptive analysis page of PKVS prototype, list down the recommendation based on predictive analytic result. The system will produce the knowledge base on the solutions of internet usage activities and propose 3 highest weighted recommendations to the user (decision maker). By giving the recommendation, decision maker can quickly make decision from option given.

5.4 Summary

This chapter describes the process of turning the proposed conceptual model to a physical artifact, i.e PKV prototype. This achieved a web-based PKVS prototype which is developed to handle the issue of student performance based on IUB in IHL dataset. The successful implementation of the proposed model in achieving the prototype validates its applicability. The heuristic evaluation is on the usability and data representation correctness of the developed prototype will explained in details in chapter six. In the next chapter, the evaluation and results of the PKV model, PKVS prototype and knowledge-base are presented with its findings.

CHAPTER SIX

EVALUATION AND RESULTS

6.1 Introduction

This chapter represents the formative evaluation of the proposed conceptual model. The expert review and their findings are reported through model verification stage 1 and stage 2. Lastly, the prototype was examined through usability testing. This is also to determine the suitability of the proposed model in the design and development of KV in the IHL domain. Lastly, the model validation was conducted with the knowledge base model validation.

6.2 Model Verification

The conceptual design model was firstly verified using expert review. This study uses the expert review technique on evaluating and verifying the proposed PKV model. The experts, as referred to in this study are academicians who are experts in analytic and have prior experience in developing visualization tools. This evaluation is an extensive and iterative process and is discussed in the next section. Next section discussed the finding of the PKV model from model verification stage 1 with experts, model refinement and model verification stage 2 with experts. Figure 6.1 is the PKV model (before refinement).

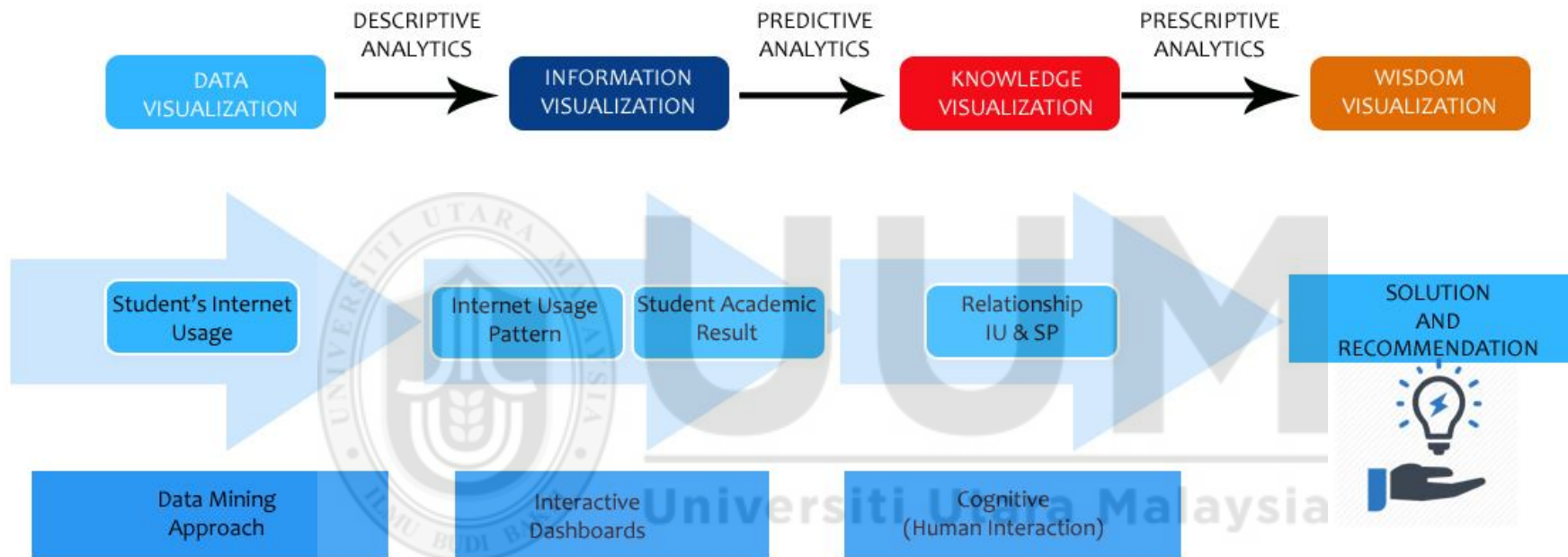


Figure 6.1. The PKV Model (Before Refinement)

6.2.1 PKV Model Verification 1

The PKV model verification was conducted by expert review method after the instrument was successfully validated. The expert review is recognized as a way of improving the quality of the developed conceptual model (Wieggers, 2002). According to Morgan (1996), the expert review is one of the accepted techniques used to verify the appropriateness of the proposed model. The expert review was done by considering the appropriateness of the proposed model using measurement and dimensions adapted from Syamsul (2011), Hecksel (2004), and Kerzner (2006). Hence, this study uses the expert review technique to verify the PKV model. As mentioned in Chapter 3, three experts are adequate to review the proposed PKV model. Three (3) experts are chosen based on areas of specialities align with this study. The demographics profiles of experts that participated in the model review session are presented in Table 6.1.

Table 6.1.
Demographic Profiles of Experts in Model Verification

No.	Qualifications	Gender	Expertise	Year of Experience
Expert A	PhD in Computer Science	Male	Information Analytics	30 years
Expert B	PhD in Software Engineering	Male	Data Warehousing, Intelligent Database, Data Structures	27 years
Expert C	PhD in Computer Science	Female	Machine Learning, Data Mining, Predictive Analytics	19 years

From the table above, three experts from academicians who have more than 15 years' experiences are involved in model verification. The experts, as referred to in this

study are academicians who is experts in analytic and have prior experience in developing visualization tools.

6.2.1.1 Findings

Data gathered from the expert review are tabulated in Table 6.2. The data were documented as in frequency of responses of the expert review to the questions asked in the instrument. As shown in the table, the mean values of the experts' findings showed they all align with "Strongly Agree". The total mean values from the 7 questionnaires are Expert A (6.66), Expert B (5.10), and Expert C (7.06).

Table 6.2.
Mean Values of the Expert Review Findings of PKV Conceptual Model

Dimensions	Expert A	Expert B	Expert C	Mean
Q1- Complexity	5.20	5.40	5.40	5.33
Q2- Visibility	6.50	5.75	4.75	5.67
Q3- Flexibility	7.30	5.00	8.30	6.88
Q4- Clarity	6.67	4.67	5.00	5.45
Q5- Manageability	7.75	4.50	7.00	6.42
Q6- Practicality	8.00	5.00	9.00	7.33
Q7- Effectiveness	5.20	5.40	10.00	6.87
Mean (All Experts)	6.66	5.10	7.06	6.28

As clearly indicated in Table 6.2, all scores for the dimensions are relatively high with at least 5.33 out of the rank of 10. The majority of the experts agreed that the proposed model contain relevant phases and components, exhibit logical flows, phases is clear and well understood and usable to be applied in the context of education sector. The highest mean score among the dimensions is practicality with value 7.33, and the lowest is complexity with the value 5.33. This implies that the PKV model produces result that can be used for future improvement and this model

is practical to be implemented in the real world. However, the proposed model has weaker points in term of complexity. One of the experts think that connections and flows of all phases and used in the proposed model are not clear, therefore, it needs to have better in-line.

Besides responses in frequency, experts also provide written comments. Experts also suggest some elements to be added in content structure components and changed terminologies to give clearer meaning. The experts noted the chosen theories and link that found to build this model. This review was taken into consideration in revising the proposed model. Table 6.3 lists the comments from all the experts. Some of the comments were rephrased from the original versions to express clearer meaning.

Table 6.3.
Further Comments from the Expert Reviews

No	Experts	Comments and Suggestions
1	Expert A	➤ Should be interconnections between the various stages. ➤ The concept of prescriptive analytics may need to be revised in details.
2	Expert B	➤ Rediagram the PKV model by showing step by step of the process. In each process need to show input and output. For example input can be data and output can be a model/diagram. ➤ Need to use optimization algorithm to rank the recommendation.
3	Expert C	➤ Need to compare the prescriptive flow against the ones reported in medical and business domain. ➤ Should focus on the visualization process as to portray the title of the project

In line with above comments and suggestions, as well as to make the model clearer in terms of flow and the connection between components and phases. Hence, from the comments it can be concluded that majority of the experts inquired for design/development in an appropriate form. They want the model should interconnect between each phase and highlights the important process to portray the specific concepts that want to convey. Among of the expertise, two of them also gave advice on adding some features to the process of the model design which is taken into consideration. Besides that, two of the experts agreed that the proposed model phases and components which contain relevant elements, well understood and suitable to be applied in the context education domain.

In Figure 6.2 clearly illustrates a radar graph which gives further valuable illustration to the means scores on expert-by-expert basis. Overall mean value from the 3 experts gives the highest value to practicality (mean = 7.33) and agree that using the proposed model is practical to be implemented in the real world and produces results that can be used for future improvement. But the lowest value in terms of complexity with (mean= 5.33), meaning that the model needs to improve in term of design and make it easy to understand. The radar is not balancing, as we can see only one of the experts have the balancing radar draft which is Expert B. The mean score for every dimension is around 4 to 6. Expert B also gave lowest scores to flexibility where other experts' scores rank higher than others. There is no consistent pattern that could relate the experts' scores with either their core areas of specialization or years of experience.



Figure 6.2. Radar Graph for the Expert Review Findings

From the model verification analysis from expert review, it can conclude that the proposed conceptual model is verified to be satisfactory but need certain improvement in term of design/development and should more focus on visualization part. The important feedback from the expert is the need to explicitly state and need for model refinement based on the comments.

6.2.2 PKV Model Refinement

As regards iteration in the verification process in model development, the majority of the experts (expert review), agreed that the development process is clear and useful as a guide PKV prototype development to be develop for education environment. However, there are some comments and suggestions from the experts to improve the sequence in the development process. there were comments and suggestions from the experts to improve the model. The comments and suggestions were categorized into four subthemes: 1) model organization, 2) model phases, 3) model components, and 4) model process. They gave suggestions and valuable comments that were taken into consideration in the refinement the proposed PKV model. Accordingly, these

suggestions and comments were used iteratively to refined the proposed PKV design model as shown in Table 6.4.

Table 6.4.
Comments and Suggestions from the Expert Reviews

Elements	Refinement	Experts
Model Organizations	How the organization of the model?	
	- Need to organize the analytic part. - Need to clearly drawn to reflect the understanding of the connection.	Expert A
Model Phases	The phases in the proposed model are clear?	
	- Need to interconnect between the various stages.	Expert A
Model Components	All the concepts and components are clear?	
	- Need to add optimization	Expert C
Model Process	Steps or process included are easy to apply?	Expert A,B and C
	- Steps are easy to apply - Rediagram the PKV model by showing step by step of the process. - Each process show the input and output.	Expert B
		Expert B

From the comments depicted in Table 6.4, it can be concluded that majority of the experts inquired for design and develop PKV model agreed that all the model organizations, phases, components and process are well organizing and clear. The

expertise gives some comments to well organize the model and add some phases into the model. For the first phase of PKV model, the correction was done according to comments and suggestions regarding flows, connection, and others from experts. Figure 6.3 is the PKV model after refinement. Next section, model verification stage 2 was conducted after refinement model to thoroughly verified the model before validation process.



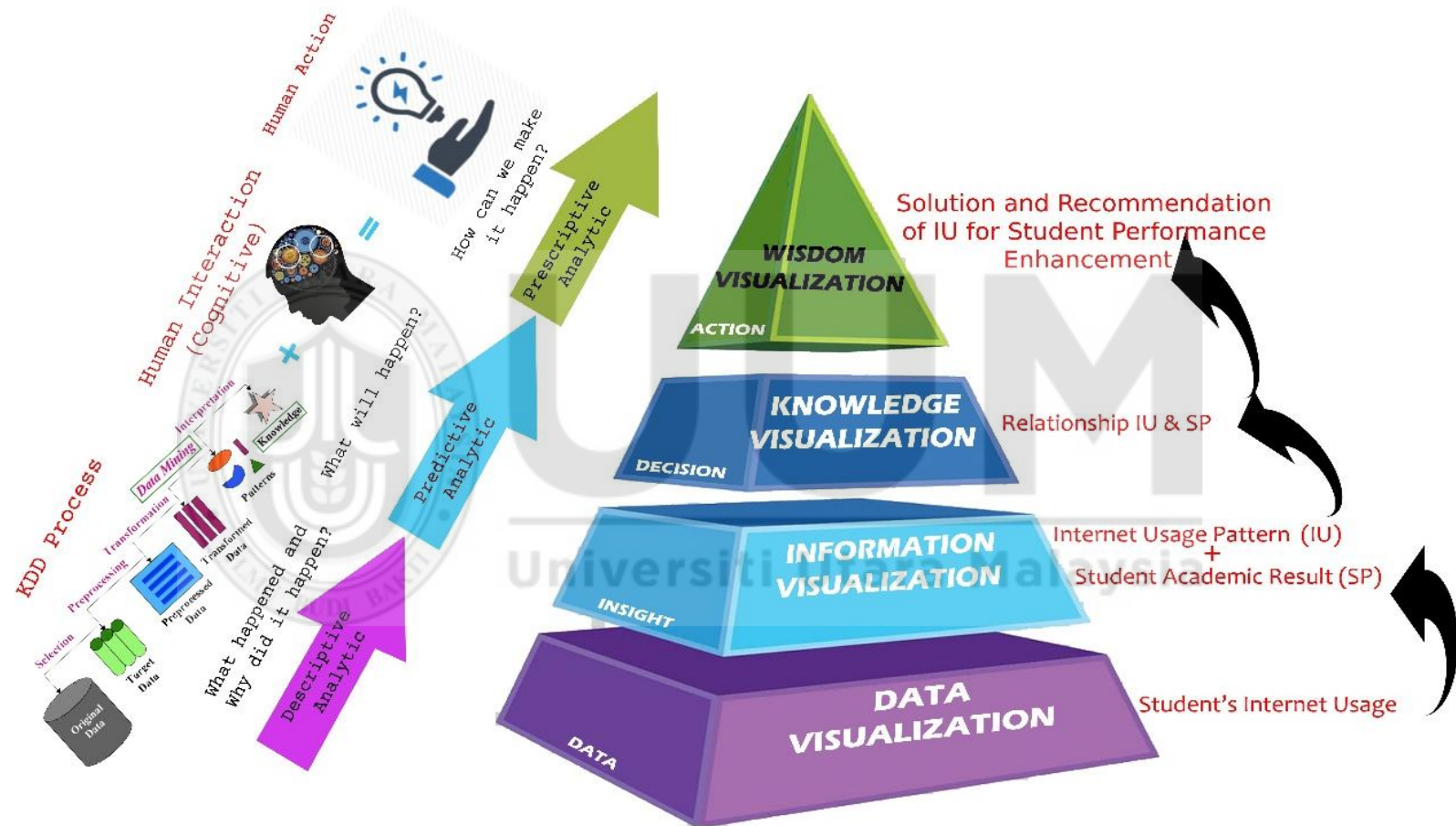


Figure 6.3. The PKV Model (After Refinement)

6.2.3 PKV Model Verification 2

After model refinement, the model verification stage 2 is conducted with another three (3) expertise. 3 expertise are adequate to verify the proposed PKV model for the stage 2. The 3-expertise come from computer engineering and computer science who has more than 10 years' experience in this field. The demographics profiles of experts that participated in the model review session are presented in Table 6.5.

Table 6.5.

Demographic Profiles of Experts in Model Validation

Experts	Qualifications	Gender	Expertise	Year of Experience(s)
Expert D	PhD in Computer Science	Female	Computational linguistics, artificial intelligence, machine learning and content-based information retrieval.	11 years
Expert E	PhD in Computer Science	Male	Software Engineering and Information System Development.	14 years
Expert F	PhD in Software Engineering	Male	software engineering, empirical software engineering, mining software repository, social network analysis, socio-technical congruence, computer supportive collaborative work, and software process	14 years

6.2.3.1 Findings

Data gathered from the expert review are tabulated in Table 6.6. The data were documented as in frequency of responses of the expert review to the questions asked in the instrument.

Table 6.6.

Mean Values of the Expert Review Validation of PKV Conceptual Model

Dimensions	Expert D	Expert E	Expert F	Mean
Q1- Complexity	8.80	10.00	9.00	9.27
Q2- Visibility	8.75	10.00	8.75	9.17
Q3- Flexibility	8.30	8.67	8.67	8.55
Q4- Clarity	9.00	10.00	10.00	9.67
Q5- Manageability	8.75	9.25	10.00	9.33
Q6- Practicality	8.00	10.00	10.00	9.33
Q7- Effectiveness	8.00	8.20	9.40	8.53
Mean (All Experts)	8.51	9.45	9.40	9.12

As shown in the Table 6.6, the mean values of the experts' findings showed they all align with "Strongly Agree". The total mean values from the 7 questionnaires are Expert D (8.51), Expert E (9.45) and Expert F (9.40). The total average value from 7 questionnaires and from 3 expertise is 9.12 is greater than the average value from model verification stage 1 which is 6.28. From the results, as clearly indicated in Table 6.6, all scores for the 7 dimensions are relatively high with at least 8.53 out of 10. Out of 7 dimensions, the highest value is clarity with value (9.67) and it implies that the proposed model is easily followed, all the activities included are easy to apply and the model is workable as a whole. However, the PKV model has lowest points in term of effectiveness, but the value is acceptable based on Hecksel (2004). The majority of the experts agreed that the proposed model contain relevant phases and components, exhibit logical flows, usable to the development in education sector and the phases and their components are readable.

Lastly, they were expected to give overall comments based on their understanding and perception of the clarity, phases, connections, and flow of the proposed PKV model as illustrate in Table 6.7.

Table 6.7.
Further Comments of PKV Conceptual Model

Experts	Comments and Suggestions
1 Expert D	➤ General idea of the proposed model is clear and well understood, thus it is believed that the proposed model is suitable to be applied in the context of education sector.
2 Expert E	➤ Overall, the model phases and their components are easily understood but might some of them need to demonstrate in more details.
3 Expert F	➤ The model is easy to follow and applied and it is good for decision maker to make decision specially to improve student performance.

Hence, from the comments it can be concluded that majority of the expertise agreed that the phases of model is well understood, easy to understand and practical to implement in the real world. Overall, the proposed conceptual model is verified to be excellent and certified for prototype development.

Based on the comments by the experts depicted in Table 6.4, there were enhancement that has been done for the PKV model. For the first phase of PKV model, the enhancement was done according to comments and suggestions that has been categorized into four phases: 1) Model organization, 2) Model Phases, 3) Model Components, and 4) Model Process.

1) Model Organization

In this phase, the PKV model has been redesign horizontal to vertical by using hierarchical representation. This hierarchical representation can provide a simple and

intuitive way to introduce the PKV model by following the DIKW model as a base model. This hierarchy suggests that wisdom is built upon knowledge, which, in turn, is built upon information, and information is derived from data.

2) Model Phases

For the model phases, all the components of the PKV model are improved by dividing into three main components that belong to 10 subcomponents that interconnected between the various stages. The components enhance in this PKV model are the visualization hierarchy that consist of DV, InfoVis, KV and WV, analytic component in term of descriptive, predictive and prescriptive analytic, and the last components is cognitive by interconnect between KDD, human interaction and human action into a single model. These three components interconnected since their role as complementary aspects of the information processing and decision-making process. Each component plays a crucial role in enhancing human understanding and problem-solving capabilities

3) Model Components

Continuous from the model phases that the PKV model interconnected between three components and consists of ten subcomponents. These three components which are visualization, analytics, and cognition are interconnected in the sense that they work together to improve human understanding and decision-making processes. Visualization enhances the cognitive processing of information by presenting data in a more accessible format. Analytics provides the necessary knowledge and insights that support cognitive reasoning and problem-solving. Together, these components create a symbiotic relationship, empowering individuals to make more informed decisions and gain deeper insights from complex data. These steps are showed in the

enhancement PKV model by showing step by steps of the process and how they connected each other through the process.

4) Model Process

Systematic mapping....In this stage, the PKV model enhance by showing the step by step of the process based on the context study which is to study the impact of student performance based on IUB and prescribe the recommendations based on the results. All the flows explain in details in every process of visualization hierarchy, and how the analytic involve in this process and how the cognitive take place after the process.

Figure 6.4 is the revision of the PKV model before refinement and after refinement.

Next section will discuss in details the prototype development process.



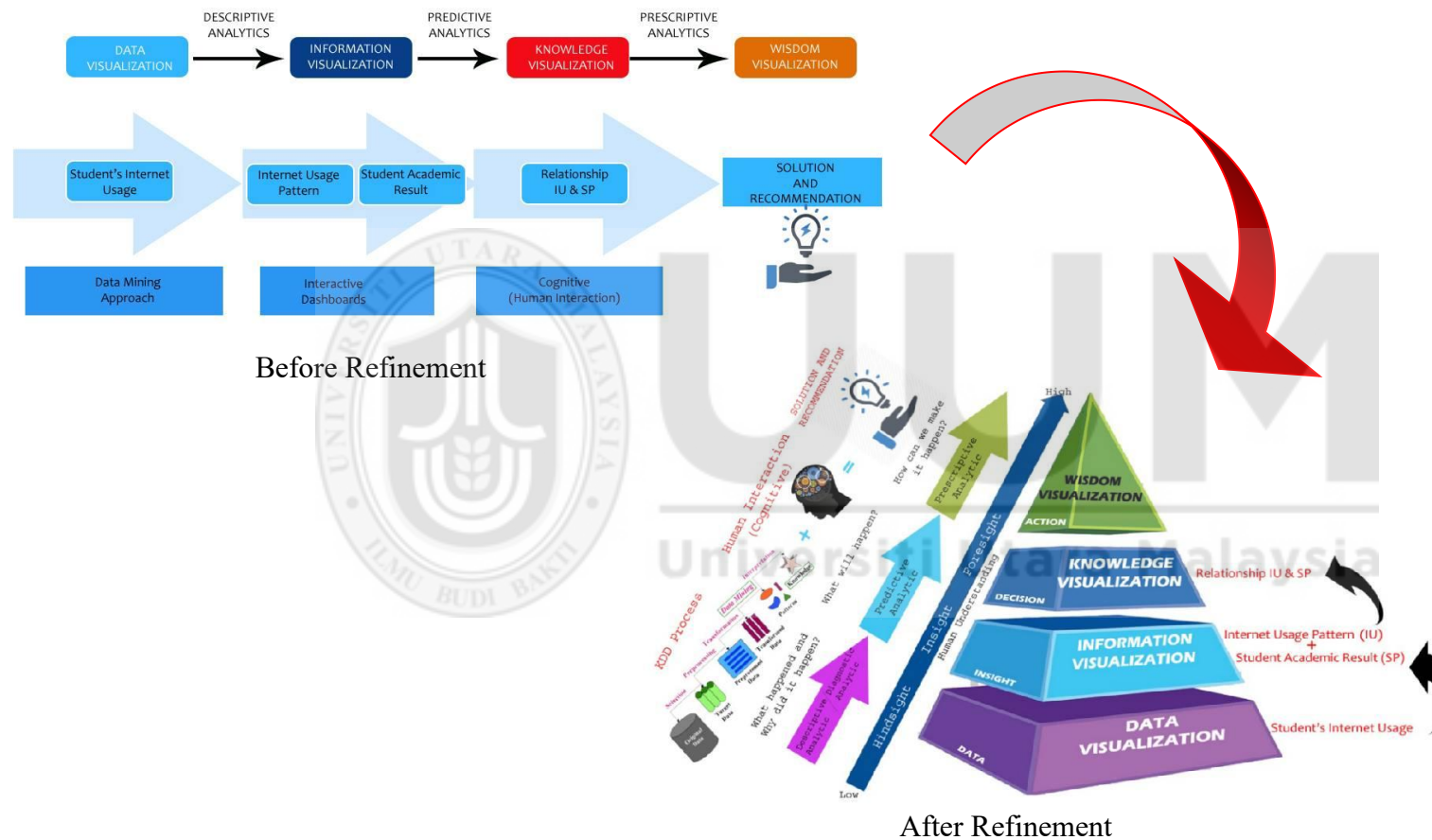


Figure 6.4. PKV Model Before Refinement and After Refinement

6.3 Prototype Evaluation (Usability Testing)

The usability testing for the PKVS prototype was conducted after the instruments successfully validated. The measurements were made through an instrument named Q-U, which comprises of five main dimensions, visibility, flexibility, learnability, application behavior, and real-time decision making as usability attributes. During the usability test, 11 respondents consist of 9 practitioners with IT backgrounds and 2 respondents from decision maker was participated. The overall Q-U instrument is finalizing and send to the respondents to answer all the questions after trying the PKVS prototype.

Descriptive statistics was used in order to describe the basic features of the data in this study, to provide summaries about the sample and the measures, together with graphic analysis and to form the basis of virtually every quantitative analysis of data. The justification for using descriptive statistics is because it is useful to summarize the group of data using a combination of tabulated description (i.e., tables), graphical description (i.e., graphs and charts) and statistical commentary (i.e., a discussion of the results). Moreover, the findings are adequately discussed in the next sections.

6.3.1 The Visibility of PKV Prototype

As clearly indicated by the Figure 5.4 and Table 5.5 that all respondents agreed that the PKV prototype is able to extract useful information. Particularly, the majority of respondents with 100 % strongly agree confirm that PKV prototype can display the information (virtual results) in a well-structured. Also for the item 2, majority respondents strongly agree (100%) that all instructions in the prototype are visible and self-explanatory. Regarding the navigation options in the PKV prototype, the finding shows that 36.36% are agree that the navigation options such as (Links,

shortcuts, home, back, forward, etc.) are displayed in a visible manner. Majority of the respondents choose neutrality with 54.54%, while 9.09% of them disagree and think that navigation options are displayed invisible manner. Likewise, all respondents with 45.45% strongly agree and 54.54% agree found that PKV prototype affirmed that the data in PKV prototype is concisely presented.

Furthermore, the majority of respondents (45.45% strongly agree and 36.36% agree) state that the PKV prototype meets the user expectation in terms of functions and capabilities, while 18.18% of them took the side of neutrality. Noteworthy, majority respondents strongly agree (54.54%) and agree (45.45%) that the PKV prototype has an accepted interface. On the same aspect, 90.91% strongly agree and 9.09% agree stated that the PKV prototype has a pleasant interface. The majority of respondents with 27.27% strongly agree and 45.45% agree found that the organization information in PKV prototype visualizes in a clear manner; while 27.27% of them took the side of neutrality. All the findings above are supported by the bar chart and statistics in Figure 6.5 and Table 6.8.

Table 6.8.
The Visibility of PKV Prototype

Visibility Items	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean	Std. Deviation	Total
Item 1	N= 11 100%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	5.00	0	11
Item 2	N= 11 100%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	5.00	0	11
Item 3	N= 00 0.00%	N= 04 36.36%	N= 06 54.54%	N= 01 9.09%	N= 00 0.00%	3.27	0.647	11
Item 4	N= 05 45.45%	N= 06 54.54%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	4.45	0.522	11
Item 5	N= 05	N= 04	N= 02	N= 00	N= 00	4.27	0.786	11

	45.45%	36.36%	18.18%	0.00%	0.00%			
Item 6	N= 06	N= 05	N= 00	N= 00	N= 00	4.55	0.522	11
	54.54%	45.45%	0.00%	0.00%	0.00%			
Item 7	N= 10	N= 01	N= 00	N= 00	N= 00	4.91	0.302	11
	90.91%	9.09%	0.00%	0.00%	0.00%			
Item 8	N= 03	N= 05	N= 03	N= 00	N= 00	4.00	0.775	11
	27.27%	45.45%	27.27%	0.00%	0.00%			

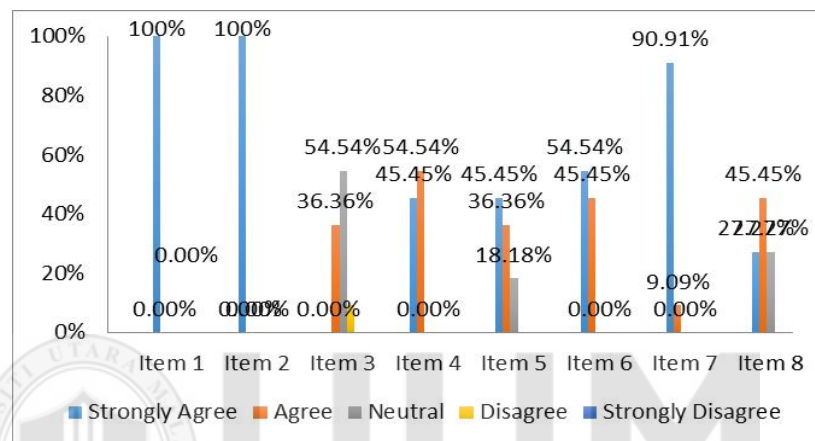


Figure 6.5. The Graph of the Visibility for PKV Prototype

On the same aspects, the descriptive analysis presented in Figure 6.6 shows the mean values for each measurement item are greater than 3 indicating that the respondents agreed with the statement for each measurement item, hence, the respondents have positive reaction about the PKV prototype usability in terms of visibility; and thereby strengthens the conclusion. The implication of this finding is that PKV and its prototype are visible.

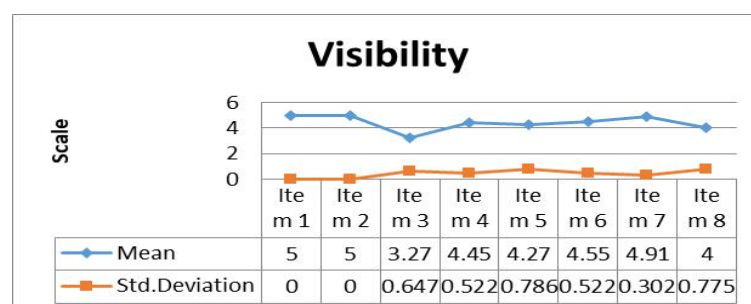


Figure 6.6. The Descriptive Statistic of PKV Prototype Visibility

6.3.2 The Flexibility of PKV Prototype

The results reveal that the PKV prototype is neutrality flexible. Particularly, the majority of the respondents tend to neutrality with 54.54% feeling in control during usage of PKV prototype; while 27.27% strongly agree and 18.18% respondents choose agree. Besides, the 100% of the respondents' neutrality choose that the PKV prototype has customizable feature. Again, to the data entry in PKV prototype, the finding shows that 100% of the respondents believe and stay in the neutral side. Furthermore, the majority of the respondents stay neutral with 90.9% choose neutral and only 9.09% agree that by using PKV prototype the data can be used, manipulated, and processed in an easy manner. All aforementioned findings are supported by the bar chart and statistics in Figure 6.7 and Table 6.9. From the results, it can conclude that the PKV prototype is neutrally flexible.

Table 6.9.
The Flexibility of PKV Prototype

Flexibility Items	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean	Std. Deviation	Total
Item 1	N= 03 27.27%	N= 02 18.18%	N= 06 54.54%	N= 00 0.00%	N= 00 0.00%	3.73	0.905	11
Item 2	N= 00 0.00%	N= 00 0.00%	N= 11 100%	N= 00 0.00%	N= 00 0.00%	3.00	0.00	11
Item 3	N= 00 0.00%	N= 00 0.00%	N= 11 100%	N= 00 0.00%	N= 00 0.00%	3.00	0.00	11
Item 4	N= 00 0.00%	N= 01 9.09%	N= 10 90.91%	N= 00 0.00%	N= 00 0.00%	3.09	0.302	11

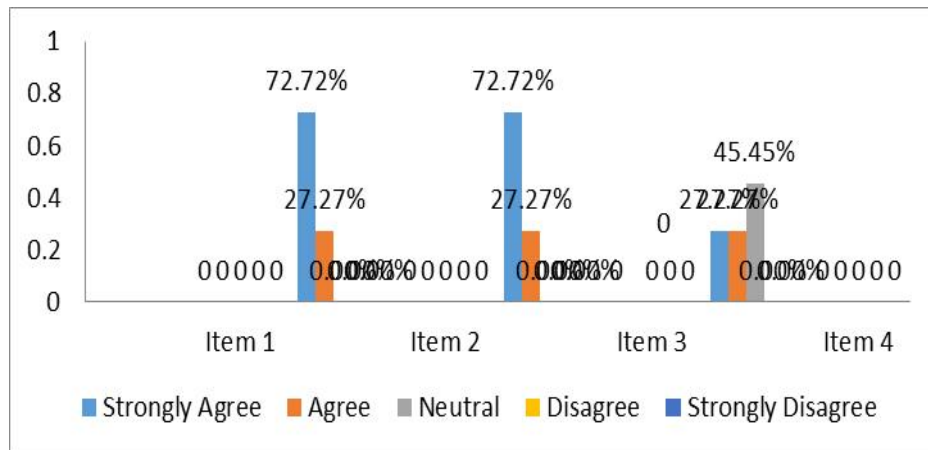


Figure 6.7. The Graph of the Flexibility for PKV Prototype

On the same aspects, the descriptive analysis presented in Figure 6.8 showed the mean values for each measurement item are greater than 3 but not reach 4 indicating that the respondents are neutrally with the statement for each measurement item of the PKV prototype usability in terms of flexibility; and thereby strengthens the conclusion. The implication of this finding is that PKV and its prototype are workable in practice in term of flexibility. Besides, the standard deviation values for each measurement item are less than 0.8, this indicates how close to the average the data is clustered.

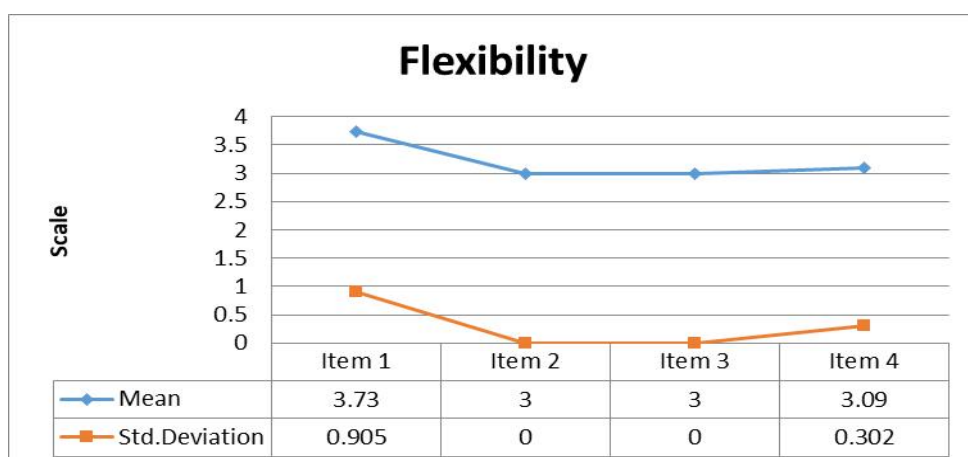


Figure 6.8. The Descriptive Statistic of PKV Prototype for Flexibility

6.3.3 The Learnability of PKV Prototype

As clearly indicated by the Figure 6.9 and Table 6.10, the results reveal that the learnability is high. The majority of the respondents with 72.72% strongly agree and 27.27% is agree found the data grouping of PKV prototype is reasonable for easy learning. None of the respondents disagree with the item 1. Again, the same percentage also agree (72.72% strongly agree and 27.27% agree) respectively. Majority of the respondents agree that the PKV prototype promotes learnability to make it accessible for infrequent usage. Regarding the grouping of menu options in PKV prototype, the finding shows most of the respondents (27.27% strongly agree and 27.27% agree) think that it is logical; while 45.45% tend to neutrality. Eventually, majority of respondents with high strongly agree (81.81%) and 18.18 % are agree found that by using PKV prototype could become productive quickly. All aforementioned findings above are supported as shown in the bar chart and statistics in Figure 6.9 and Table 6.10.

Table 6.10.
The Learnability of PKV Prototype

Learnability items	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean	Std. Deviation	Total
Item 1	N= 08 72.72%	N= 03 27.27%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	4.73	0.467	11
Item 2	N= 08 72.72%	N= 03 27.27%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	4.73	0.467	11
Item 3	N= 03 27.27%	N= 03 27.27%	N= 05 45.45%	N= 00 0.00%	N= 00 0.00%	3.82	0.874	11
Item 4	N= 09 81.81%	N= 02 18.18%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	4.82	0.405	11

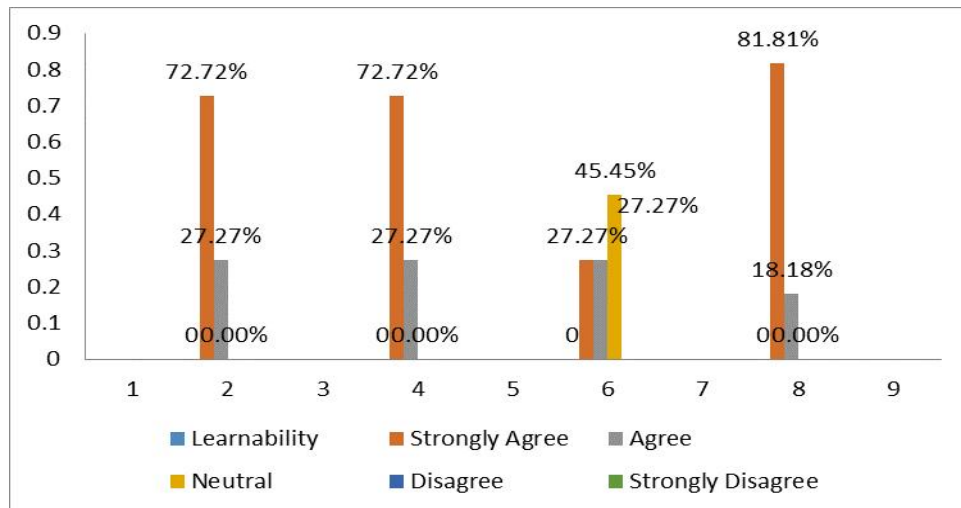


Figure 6.9. The Graph of the Learnability for PKV Prototype

On the same aspects, the descriptive analysis presented in Figure 5.9 showed the mean values for each measurement item are greater than 4 this indicating that the respondents agreed with the statement for each measurement item, hence, the respondents have a positive reaction about the PKV prototype usability in terms of learnability; and thereby strengthens the conclusion. The implication of this finding is that PKV and its prototype are highly learnable. Besides, the standard deviation values for each measurement item are less than 0.8. This indicates how close to the average the data is clustered.

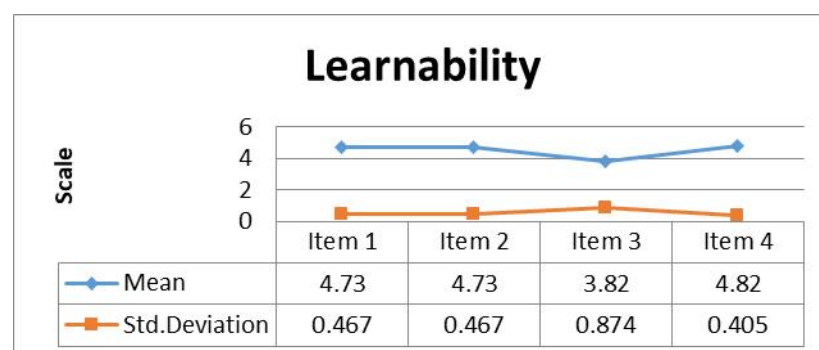


Figure 6.10. The Descriptive Statistic of PKV Prototype Learnability

6.3.4 The Application Behavior

The findings indicate that the respondents (36.36% strongly agree and 27.27% agree) that by using PKV prototype will enhance their efficiency through a consistently

rapid response rate, only 36.36% of the respondents stay neutrality. Likewise, all respondents (54.54% and 18.18%) either strongly agree and agree respectively, believes that the PKV prototype is consistent, but 27.27% of them tend to neutrality. Besides, the majority of respondents with 100% for strongly agree think that the information provides by PKV prototype was effective in helping them complete the tasks. In regard to the availability of information, the majority of respondents (54.54% strongly agree and 45.45% agree) think that by using PKV prototype it was easy to find, none of them preferred to be in neutral. Also, the majority of the respondents (90.91% strongly agree and 9.09% agree) believe that they are able to complete the tasks quickly via using PKV prototype. Refer to Figure 6.11 and Table 6.11.

Table 6.11.
The Application Behavior of PKV Prototype

Application Behavior	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean	Std. Deviation	Total
Item 1	N= 04	N= 03	N= 04	N= 00	N= 00	4.00	0.894	11
	36.36%	27.27%	36.36%	0.00%	0.00%			
Item 2	N= 06	N= 02	N= 03	N= 00	N= 00	4.27	0.905	11
	54.54%	18.18%	27.27%	0.00%	0.00%			
Item 3	N= 11	N= 00	N= 00	N= 00	N= 00	5.00	0.000	11
	100.00%	0.00%	0.00%	0.00%	0.00%			
Item 4	N= 09	N= 01	N= 01	N= 00	N= 00	4.73	0.647	11
	81.81%	9.09%	0.00%	0.00%	0.00%			
Item 5	N= 06	N=05	N= 00	N= 00	N= 00	4.55	0.522	11
	54.54%	45.45%	0.00%	0.00%	0.00%			
Item 6	N= 10	N= 01	N= 00	N= 00	N= 00	4.91	0.302	11
	90.91%	9.09%	0.00%	0.00%	0.00%			

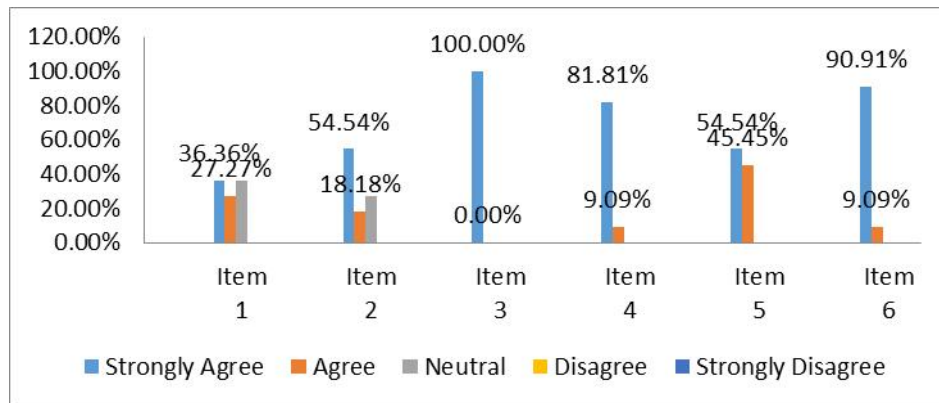


Figure 6.11. The Graph of the Application Behavior for PKV Prototype

On the same aspects, the descriptive analysis presented in Figure 6.12 showed the mean values for each measurement item are greater than 4 this indicating that the respondents agreed with the statement for each measurement item, hence, the respondents have a positive reaction about the PKV prototype usability in terms of application behavior; and thereby strengthens the conclusion. Besides, the standard deviation values for each measurement item are less than 09, which indicates how close to the average the data is clustered.

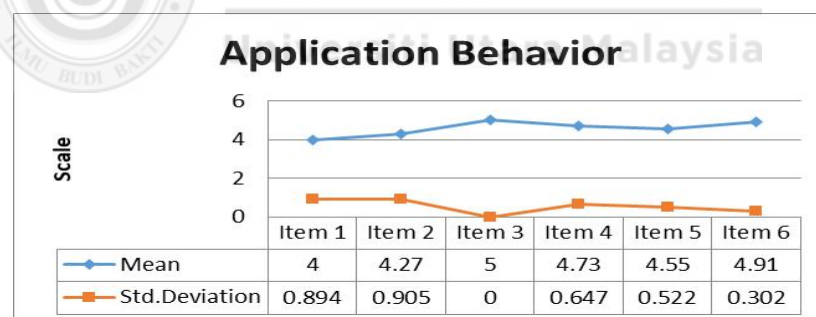


Figure 6.12. The Descriptive Statistic of PKV Prototype for Application Behavior

6.3.5 Real-Time Decision Making

As clearly indicated by the results visualize in Table 6.12, that the PKV prototype is able to provide real-time data for decision-making. Particularly, the majority of the respondents (63.63% strongly agree and 36.36% agree) agree that the knowledge sharing is allowed in PKV prototype. Likewise, most of the respondents agree respectively with 54.54% for agree, that PKV prototype assists the decision-making

process by providing the information visualization functionality (comparison charts, graphs in revealing trends etc.); but 45.45% tend to neutrality. Besides, the majority of the respondents (63.63% strongly agree and 36.36% agree) believe that PKV prototype provides sufficient coverage for all data resources. Furthermore, all the respondents are strongly agree affirm that PKV prototype provides data on time to take suitable actions and decisions. likewise, all the respondents (81.81% strongly agree and 18.18% agree) affirm that the data provided by PKV prototype are always live data and up to date, which means PKV proposed model and its prototype provides fully supported for real-time decision-making. Refer to Figure 6.13 and Table 6.12, which affirmed that the PKV prototype is believe to provide real-time data for decision making.

Table 6.12.
The Real-Time Decision Making of PKV Prototype

Real-Time Decision Making	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean	Std. Deviation	Total
Item 1	N= 07 63.63%	N= 04 36.36%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	4.64	0.505	11
Item 2	N= 00 0.00%	N= 06 54.54%	N= 05 45.45%	N= 00 0.00%	N= 00 0.00%	3.55	0.522	11
Item 3	N= 07 63.63%	N= 04 36.36%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	4.27	0.786	11
Item 4	N= 11 100.00%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	5.00	0.00	11
Item 5	N= 09 81.81%	N= 02 18.18%	N= 00 0.00%	N= 00 0.00%	N= 00 0.00%	4.82	0.405	11

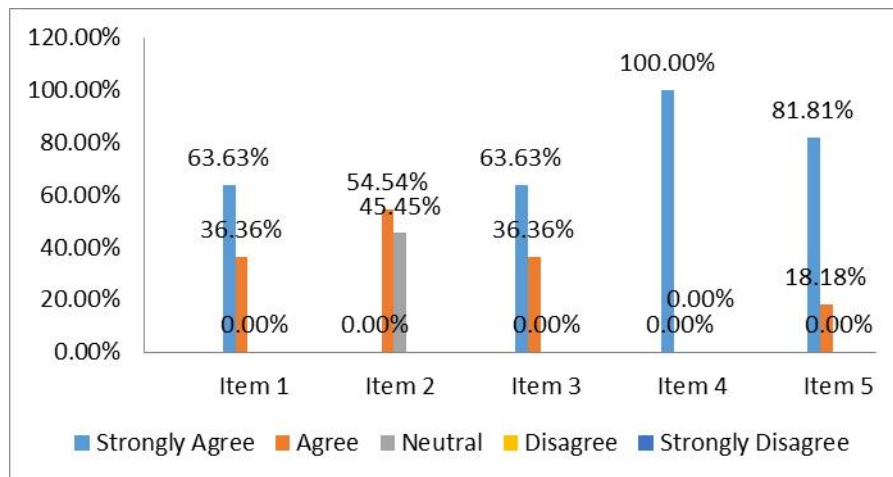


Figure 6.13. The Graph of the Real-Time Decision Making for PKV Prototype

On the same aspects, the descriptive analysis presented in Figure 6.14 showed the mean values for each measurement item are greater than 3 indicating that the respondents agreed with the statement for each measurement item, hence, the respondents have a positive reaction about the PKV prototype usability in terms of real-time decision making, and thereby strengthens the conclusion. Besides, the standard deviation values for each measurement item are less than 0.8, which indicates how close to the average the data is clustered.

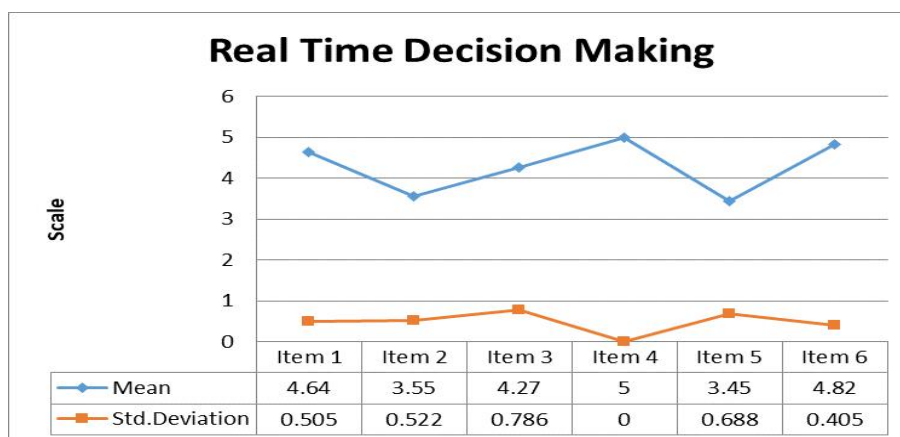


Figure 6.14. The Descriptive Statistic of PKV Prototype for Real-Time Decision Making

6.3.6 The Overall Usability Findings

In order to obtain the overall finding, the average of findings for each usability attribute was calculated. The overall usability is made of five dimensions as depicted in Table 6.13 and Figure 6.15.

Table 6.13.
The Overall Usability Finding

No.	Usability Dimensions	Mean
1.	Visibility	46.58
2.	Flexibility	45.35
3.	Learnability	50.00
4.	Application Behavior	59.09
5.	Real-Time Decision Making	71.84
The Average		54.57

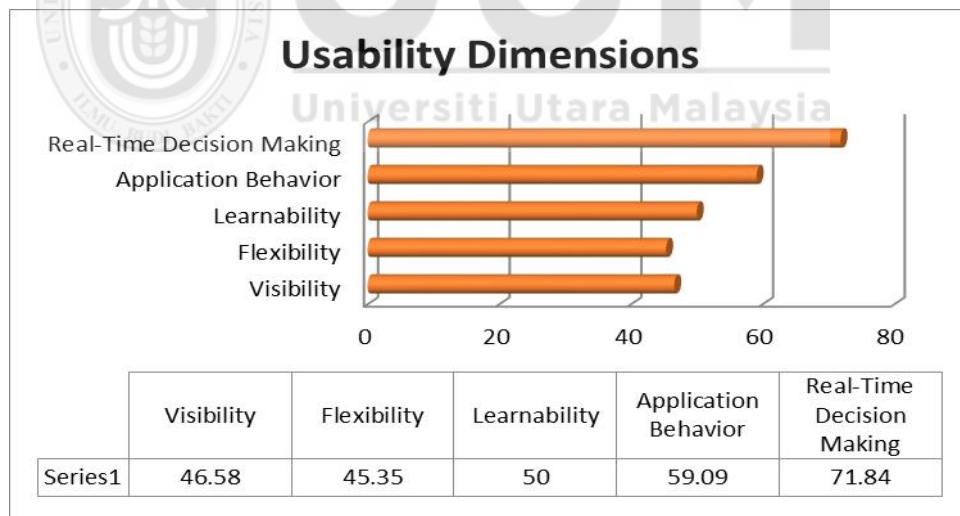


Figure 6.15. The Overall of the Usability Finding of PKV Prototype

Calculating the average agreement value for each dimension, the figure shows that for each dimension, the majority of respondents agree that the PKV prototype provide data visibility, flexible in terms of process, easy to learn, behave as expected,

provide necessary error control and help, and allow real time decision making. Overall, on total average 54.57% of the respondents agree to this.

6.4 Model Validation

Expert review are one of the accepted techniques used to evaluate and validate the proposed model on a matter determined by the researcher (Morgan, 1996). Hence, the expert reviews were conducted to validate the model after the refining process model. In this study, the model validated through the process of knowledge base creation. After model development as discussed in details in Chapter, the model was verified by using expert review through the verification process. Once the model is successfully verified, the prototype was developing as a proof of concept of the PKV model. In the prototype, the three stages analytics; descriptive, predictive and prescriptive were applied along with the visualization tools. In the system itself, knowledge base was created by using prescriptive analytic. The knowledge base will use as model validation purposes in this study. This validation is an extensive and iterative process, and is discussed in the next section.

6.4.1 Knowledge Base Validation

To create a PKVS prototype, it is necessary to create an internet usage rules (knowledge based). Analysis of IUB and students' CGPA yielded the data for creating a prototype. Knowledge based rules are depicted after gone through all the analytic process, starting from descriptive, predictive and prescriptive analytics. Table 6.14 gives a fragment of the set of rules for the IUB and Student Performance.

Table 6.14.
Knowledge Based “If ..., Then ...” Rules

No	Rules	Input	Output
1.	If File Transfer is increase 0.9%, then Student Performance increases 76%.	0.009*X2	0.7606
2.	If File Transfer is decrease 3.32% AND Entertainment is decrease 3.19%, then Student Performance increase 74.74%	-0.0332*X2, - 0.0319*X5	0.7474
3.	If File Transfer is decrease 3.32% AND Entertainment is decrease 2.58%, then Student Performance increase 71.94%	-0.0332*X2, - 0.0258*X5	0.7194
4.	If File Transfer is decrease 4.37%, then Student Performance increase 74.36%	-0.0437*X2	0.7436
5.	If File Transfer is decrease 4.55%, then Student Performance increase 54.59%	-0.0455*X2	0.5459
6.	If File Transfer is increase 0.08%, then Student Performance increase 98.96%	0.0008*X2	0.9896

7.	If Downloading is decrease 0.21%, then Student Performance decrease 12.58%	-0.0021*X3	-0.1258
8.	If Downloading is decrease 0.19%, then Student Performance decrease 15.26%	-0.0019*X3	-0.1526
9.	If Web Browsing is decrease 0.03% AND Social Media is decrease 0.6%, then Student Performance decrease 30.49%	-0.0003*X6, - 0.006*X7	-0.3049
10.	If Web Browsing is decrease 0.03% AND Social Media is increase 0.04%, then Student Performance increase 73.62%	-0.0003*X6, 0.0004*X7	0.7362
11.	If Web Browsing is decrease 0.04% AND Social Media is increase 0.14%, then Student Performance increase 72.89%	-0.0004*X6, 0.0014*X7	0.7289
12.	If Entertainment is decrease 0.09% AND Web Browsing is decrease 0.1%, then Student Performance increase 72.46%	-0.0009*X5, - 0.0001*X6	0.7246

	If Entertainment is decrease 0.37% AND Web		
13.	Browsing is decrease 0.02%, then Student	-0.0037*X5, - 0.0002*X6	0.7226
	Performance increase 72.26%		

	If Entertainment is decrease 0.41% AND Web		
14.	Browsing is increase 0.13%, then Student	-0.0041*X5, 0.0013*X6	0.3448
	Performance increase 34.48%		

	If Entertainment is increase 0.37% AND Web		
15.	Browsing is increase 0.02%, then Student	0.0037*X5, 0.0002*X6	0.1891
	Performance increase 18.91%		

	If Entertainment is increase 0.41% AND Web		
16.	Browsing is decrease 0.13%, then Student	0.0041*X5, - 0.0013*X6	0.5669
	Performance increase 56.69%		

After going through the prescriptive analytic, the results produced 16 sets of knowledge based. All the results contain the if-else rules for internet usage relates with students' performance. All the knowledge based are validated using expert review techniques by using open ended questions. The set of if-else rules adapted within the scope of cognitive based approach (Westra et al., 2017).

From the feedback of the experts, it was found that some of the items in the knowledge base were in line with the objectives to support decision making process. Some of the rules can be used for decision making purposes to applied in higher

education specially to improve students' academic performance through their internet usage activities.

6.4.2 Knowledge Base Model Validation

After conducting knowledge-based from prescriptive analytic, the evaluation was conducted with face validity. Three (3) experts from IHL decision and policy makers is given access to the web-based PKVS prototype. Next sub-section will explain on the findings of the knowledge base model validation.

6.4.2.1 Findings

Data gathered from the decision maker expert review are tabulated in Table 6.15. The data were documented as in frequency of responses of the expert review to the questions asked in the instrument.

Table 6.15.
Mean Values of the Expert Review Validation of PKV Model

Dimensions	Expert G	Expert H	Expert I	Mean
Q1- Correct Data Representation	9.00	10.00	9.00	9.27
Q2- Usability	9.50	10.00	8.75	9.17
Q3- Decision Support System	9.00	9.00	9.00	9.00
Q4- Knowledge Base	9.00	10.00	10.00	9.67
Mean (All Experts)	9.25	9.45	9.40	9.28

As shown in the Table 6.15, the mean values of the experts' findings showed they all align with "Strongly Agree". The total mean values from the 4 questionnaires from 23 items are Expert G (9.25), Expert H (9.45) and Expert I (9.40). The total average value from 4 questionnaires and from 3 expertise is 9.28. From the results, as clearly

indicated in Table 6.16, all scores for the 4 dimensions are relatively high with at least 9.17 out of 10. Out of 4 dimensions, the highest value is knowledge base with value (9.67) and it implies that the proposed model is producing the knowledge base that can be inverted into the system. The majority of the experts agreed that the proposed model contain the knowledge base from the prescriptive analytic results is relevant in education sector and can help decision maker make decision to improve student performance.

Lastly, they were expected to give overall comments based on their understanding and perception of the clarity, phases, connections, and flow of the proposed PKV model and PKVS prototype. The overall comments from the experts as depicted in Table 6.16.

Table 6.16.
Further Comments of PKV Model

Experts	Comments and Suggestions
1 Expert G	➤ The idea is good and relevant to the education domain. ➤ The technique and approach is highly recommended to apply in the context to help decision maker to produce suitable recommendation. ➤ General idea of the proposed model is clear and well understood, thus it is believed that the proposed model is suitable to be applied in the context of education sector. ➤ Overall the idea about the model is good and understandable.
2 Expert H	➤ The model phases and their components are understood and easy to demonstrate. ➤ The knowledge base is good and suitable in the context to improve student performance. ➤ The model is easy to follow and applied and it is good for decision maker to make decision specially to improve student performance.
3 Expert I	➤ The phases and of PKV prototype is easy to followed. ➤ The model and system is synchronizing and very good. ➤ The knowledge base is very suitable to help decision maker make decision.

Hence, from the comments it can be concluded that majority of the expertise agreed that the phases of model is well understood, easy to understand and practical to implement in the real world. Overall, the proposed conceptual model is validated to be excellent and certified for to be implemented in IHL.

6.5 Summary

The evaluation chapter shows that enhancement of KV model to improve student performance by using a cognitive and reasoning approach is possible and applicable by mapping KV and prescriptive analytic and analyzing to improve decision maker make decision based on student performance in IHL. In sum, Expert review feedbacks showed the PKV model is suitable for decision maker to improve student performance in IHL. Also, the PKVS prototype is found satisfactorily present and represent IHL students' data, usable and aid the IHL decision maker decision making process. The next chapter will give the conclusion of the whole thesis and suggest several improvements.

CHAPTER SEVEN

DISCUSSION AND CONCLUSION

7.1 Introduction

The details of research background, research objectives and research questions are discussed in Chapter 1. The research focuses on design and development of Prescriptive Knowledge Visualization (PKV) Model for decision maker in Institution of Higher Learning (IHL). Hence, to accomplish the main aim, three specific research questions were carried out:

1. What are the main components of Prescriptive Knowledge Visualization (PKV) model?
2. How to develop the Prescriptive Knowledge Visualization (PKV) model of by using cognitive and reasoning elements?
3. How to evaluate the Prescriptive Knowledge Visualization (PKV) model by using cognitive and reasoning elements?

This study formed a main aim to meet its expectation, which is to propose a conceptual model that specifies how Knowledge Visualization integrated with Prescriptive Analytic to ascertain the impact of internet usage on students' academic performance for decision maker in Institution of Higher Learning (IHL). To achieve this main objective, the following are the sub-objectives:

1. To investigate the main components of Prescriptive Knowledge Visualization (PKV) model
2. To develop the Prescriptive Knowledge Visualization (PKV) model by using cognitive and reasoning elements.

3. To evaluate the Prescriptive Knowledge Visualization (PKV) model by using cognitive and reasoning elements.

The research objectives in Chapter 1 and literatures reviewed in Chapter 2 lead to a development of PKV model. In Chapter 2 a content analysis of existing studies of Knowledge Visualization and prescriptive approaches, initiated the formation and definition of a figure of the proposed design PKV model. While in Chapter 3, the base model to develop PKV model are discussed in length. The three models are decided to build the PKV model which are Knowledge Generation Model for Visual Analytics from Sacha et al. (2014), DIKW model by Ackoff (1989) and Human Cognition Model by Green et al. (2009). In Chapter 4 discussed on the method involved to develop the PKV model which involves the three components of design research methods combined of four phases: problem definition, suggestion, development (proposed design model and prototype), and evaluation (model verification, usability testing and model evaluation). All these were translated into working prototype of PKV and were discussed in detail in Chapter 4 and 5. In addition, the prototype of the PKV were developed as proof of concept on the PKV model and was tested and evaluate by using usability testing. The development model and PKVS prototype are discussed in Chapter 5 includes the verification and validation by using expert review to test the model.

Therefore, this chapter highlights the answers of research questions, and describes the solutions proposed for each research question. In addition, this chapter also provides the summaries, discussions and describes research contributions to the body of knowledge. This chapter then ends with a discussion of future recommendation of this research, and conclusions of the study.

7.2 Overall Discussion and Conclusion

This section answers the research objectives and the research questions. There are three research questions and three research objectives are formulated to answer the questions. Obviously, the findings show that all the research questions were successfully answered through the design model and the usability testing that have been evaluated in IHL environment. Furthermore, the discussions in details for each research question will be further explained in the next sections.

7.2.1 Research Question 1

What are the main components of Prescriptive Knowledge Visualization (PKV) model?

In answering this question, few activities were conducted and have been discussed in this thesis. The main purpose of these activities was to identify components, phases, activities, and flows involved in developing the proposed model. The activities include content analysis of literature, two comparative studies one of them focused on existing Knowledge Visualization models, while the second one focused on data analytic techniques to combine in KV models. The models also being supported by other related theories. After analyzing the main components that can improve data analytic model in visualizing prescriptive knowledge, the proposed model PKV stand beyond four phases as mentioned in chapter 3, these phases named: problem definition, model suggestion, model development and model evaluation that being used. There are four phases, three main components, and ten subcomponents or the formed in the proposed model. Details of the components are presented in Chapter 4. Eventually, all these model components and subcomponents were then combined and made up the PKV design model. The proposed model with its phases, components and subcomponents were also reviewed and found well accepted by the experts. And,

therefore, the objective 1 has been achieved. The details of the 3 components and 10 subcomponents are as Table 7.1.

Table 7.1.
Components and Subcomponents of PKV Model

No	Components	Subcomponents
1	Visualization	Data Visualization
		Information Visualization
		Knowledge Visualization
		Wisdom Visualization
2	Analytic	Descriptive Analytic
		Predictive Analytic
		Prescriptive Analytic
3	Cognitive	KDD Process
		Human Interaction
		Human Action

7.2.2 Research Question 2

How to develop the Prescriptive Knowledge Visualization (PKV) model of by using cognitive and reasoning elements?

The proposed PKV model was obtained through Literature review (Chapter 2) by using content analysis technique. Content analysis technique were conducted to studies on the existing model, and relevant theories to support decision-making process to improve student performance. Three existing model were reviewed which are DIKW model, Knowledge Generation Model for Visual Analytic and Human Cognition Model. This study also reviews three theories that related to this study namely, Process Visualization Theory (PVT), Cognitive Load Theory (CLT) and

Decision Making Theory (DMT). Review of literature analyzed appropriate theories and content, gathering the requirement model and the solution to propose to solve real situation in IHL. This resulted in extraction of the model phases, model components as well as all model functions.

Finally, through an in-depth review of existing model and theories and map with the current issues and approaches, the first version of the proposed model was produced. The first version of the PKV are considering all the aspects to solve the issue of student performance in IHL. In terms of model validation, one validation methods which is expert review were conducted with the experts. Their valuable comments and corrections were added value to the proposed PKV model and has guided the modification of the first version. Finally, the final version was produced; therefore, the second objectives has been achieved.

7.2.3 Research Question 3

How to evaluate the Prescriptive Knowledge Visualization (PKV) model by using cognitive and reasoning elements?

To achieve the third objectives, the proposed model was evaluated through expert review by using model verification techniques (see section 6.2), usability testing for evaluating PKVS prototype (see section 6.3) and model validation through knowledge base (see section 6.4).

The expert review was done to verify the appropriateness the conceptual design model, the proposed techniques and the applicability of PKV design process model. The dimensions and their respective measurements for the evaluation of the model are outlined in chapter 4. An average mean value of 7.36 out of 10 as the experts ranking showed that the proposed design model is satisfactory. The ranking of each

of the dimensions which is the lowest start 6.96 in term of complexity still can be accepted as defined by Hecksel (2004). The highest average mean value under practicality with 8.00 out of 10 shows that this model can be implemented in the real world. It implies that the PKV conceptual model for IHLs' decision maker is simple, visible, flexible, clarity manageable, practical and effective among others. It also means that the specified techniques and solutions that being embedded in the model would assist in supporting IHLs' decision maker make decision to improve students' academic performance is suitable and verified.

Furthermore, the PKV prototype to strengthen the model is one of the contributions of this study. The findings from the usability testing (see section 6.3.6) showed that majority of the respondents agree that the PKV prototype provide data visibility, flexible, easy to learn, behave as expected and allow decision making process. Overall the total average 54.57% is acceptable value and can be used to measure the usability of the prototype (Shneiderman and Plaisant, 2010). The acceptability of a value to measure usability depends on the specific usability metric being used and the context in which it is applied. Usability metrics typically involve a range of scales or criteria specific to the evaluation method being employed. For example, the widely used System Usability Scale (SUS) rates usability on a scale of 0 to 100, with higher scores indicating better usability. In this case, a score above 50 is generally considered above average, and it showed that the knowledge visualization tools and prescriptive techniques are certified and suitable techniques to support decision making however there is still need improvement for the future work.

The objectives feedback from the participants suggested that the PKV prototype supports decision making activity. This is evident in decision making results with high percentage (71.84%) that the prototype support decision making. The prototype

has ability and functionality that produce actionable insights thus support decision making process. Therefore, it showed that the conceptual model is usable in designing PKV prototype that supports visibility, flexibility, learnability, application behavior and real time decision making.

7.3 Contributions of the Study

The findings produced by the current study have some valuable contributions to the existing knowledge, as well as practical point of views. This study generally contributes to Institution of Higher Learning as a domain. The following sections describe the related contributions.

7.3.1 A PKV Theoretical Contribution

Theoretically, this study has expanded the Knowledge Generation Model by Sacha et al. (2014) and DIKW model by Ackoff (1949) to a single model to describe how visualization and analytics can transfer knowledge to wisdom by using cognitive and reasoning elements. Both of these combinations are meaningful, particularly to capture the students' performance in IHL. The new technique in the cognitive-based approach is ideal for capturing knowledge from among the massive data available these days are inspired by Human Cognition Model by Green et al.(2009). Furthermore, creating new knowledge in having a role in the knowledge acquisition process using a cognitive-based approach may be a new reference for the future research field and will provide the opportunity to develop new tools for IHLs' Decision maker to support the advancement of data analysis. With the availability of prescriptive analytics, this model produce Knowledge Based system that act as an expert which contains rule-based expert systems. The role of rule-based ES can imitate the basic leadership capacity of human specialists. They are designed to solve

problems as humans do, by misusing encoded human knowledge or expertise. A rule-based ES is defined as one, which contains information obtained from a human expert, and represents that information in the form of rules, such as IF-THEN. The rule can then be used to perform operations on data to inference in order to reach the appropriate conclusion. These operations are essentially a computer program that provides a methodology for reasoning about information in the rule base or knowledge base, and for formulating conclusions. In this study, rule-based ES is based on cognitive and reasoning elements embedded in the system that produce IF-THEN rules. The impact of Internet usage to students' performance will formulate the predictive results and calling for prescriptions of solutions. It shows the techniques embedded in the model to solve decision-making issues to make a fast and valuable decision based on the results produced. The method is aligning with IHL domain specificity with a theoretical guide. It can equally be adapted to other related domains. It is also to guide IHL policy makers on the dynamics of data usage in IHL and the strength of data-driven decision-making process. The proposed PKV conceptual model is one of the most prominent theoretical contributions.

To the researcher's knowledge, this study is one of the first empirical studies that address the issue of prescriptive analytic to prescribe recommendation to solve student performance issue in IHL.

7.3.2 A PKV Practical Contribution

PKV models have been shown to have the following advantages in terms of organisational performance. The prototype is developed to solve data processing in the management of IHL students' internet usage data by practically ensuring that the study's findings are utilized. It is to be used by IHL policy-makers since they are one

of the leading decision-makers to improve students' academic performance. The practical contribution of the study model can be detailed in many points.

1. Improve accuracy of decision-making process

When it comes to make decision, decision makers inherently tend to make inaccurate decision making. After all, faster and accurate decisions conserve valuable resources, such as time consuming. As for the practical contributions, this study has shown here that by using programmed decisions which is display in visual format can help decision makers save time and make more accurate decisions. Presenting data in visual form can make it easier to comprehend, enable decision maker to obtain insights more quickly. This is the strategy that ignores part of the information loaded with the goal of making decisions more quickly, frugally and accurately than more complex methods. Considering that the use of visual format that increase the cognitive skills which will lead to better understanding. This study is built on the precept that cognitive and prescriptive analytic is new formula to weigh decision to produce better results and that, in turn, can help decision maker make accurate decision to improve students' performance based on their IUB.

2. Improve consistency of decisions

The model will help decision makers making decisions that are more consistent and improve their prescription in risky context. This is because this model has been developed based on the knowledge experts and empirical investigations of the students' performance based on students' IUB.

3. Enable exploration of more decision options

In such complex and dangerous situations, the options available to decision makers are many with unclear consequences. Thus, it would be physically

impossible for them to evaluate each option. Models developed can help in making systematic decision by evaluating these options effectiveness and support them to move away from their prior dispositions' decisions.

4. Reduce risk of decision making

Almost any human decision carries some risk that will lead to a loss or an undesirable outcome. In this model, by using the prescriptive analytic it will automatically identify and list-decision option by giving the percentages of the consequences. Decision maker can easily identify and find the option the give better consequences and low risky.

7.3.3 Knowledge Visualization in IHL Organizations

The biggest contribution in this study, the model can contribute to the benefit of IHL organizations. The proposed PKV model tackles the problem of complex decision making in higher learning specially to improve students' performance. The decision makers can rely on internal sources of information, which will help them acquire necessary insight into the problem and collaborate more effectively in order to solve the problem. If the organization is new to Knowledge Visualization, the benefits that can be obtained by using the PKV model is to demonstrate with real-world examples how they can move beyond traditional data integration and use prescriptive analytic to improve the organizations' agility.

On the other hand, prescriptive analytic has devoted much attention on representing and human knowledge and giving the right direction on suitable solution to the decision maker. The effective decision making is one of the most important activities and have the significant effect on the IHL. The success of an IHL is critically linked to effective decisions. The well-structured higher education system in Malaysia is key element to achieve its aspirations to have a resilient nation, encourage the

creation of a just society, maintain sustainable economic growth, develop global competitiveness, build a K-economy and innovative culture, strengthen human resource development and maintain sustainable environmental development.

7.4 Limitations of the Study and Recommendations for Future Works

There are few limitations encountered in this study. Even though they did not directly bear on the findings of this study, future researchers are encouraged for further improvements.

First, in the proposed model, there is a knowledge base that obtain cognitive skill by the experts. Generating a knowledge base from an expert to assist decision-makers in higher education can be beneficial. However, there are specific considerations and limitations within this context especially in term of complexity and multidimensional issues. Decision-making in higher education often involves multifaceted challenges that require an understanding of academic, administrative, financial, and social aspects. The knowledge base should be able to capture and integrate expertise from different domains to address complex issues effectively.

Furthermore, IHL vary in their mission, size, geographic location, student demographics, and institutional culture. The knowledge base should consider the contextual factors that influence decision-making, ensuring that the generated insights are relevant and applicable to specific institutional contexts. Besides that, the landscape of higher education is constantly evolving, with new methodologies, technologies, and pedagogical approaches emerging. It is crucial to ensure that the knowledge base remains up-to-date and adaptable to changes in the field.

Second, the multidimensional data embedded in the system should be centralized in exact location within IHL. This will determine the specific data object binding

system for necessary exploration and visualization in a decentralized but distributed data sources' environment.

Third, future research on a real time users, experience experimental study will be necessary to test the usability on the prototype. In this, apart from evaluating the overall functionality of the KV which this study did, task execution time can be studied. Also, perceptive data from users' reaction while interacting with the KV can be captured for further deeper insights.

In this, apart from evaluating the overall functionality of the PKV model to other industrial sector, this study can be further developed for other samples for example academic staff, alumni and courses in IHL to help the institutions improve organizational performance.

7.5 Summary

This research has proposed and produces IHL students' data internet usage and students' performance. The main aim of this study is to produce a model that will help decision maker to make fast and quality decision to improve students' performance based on their internet usage activities. For developing model strategies, therefore, this research focuses on the decision analysis that embedded knowledge visualization method and prescriptive analytic techniques to help decision maker make a strategic decision to improve students' performance in IHL. The main aim is to optimize the decisions taken by the decision maker in order to guide them in the right direction. Process Visualization Theory (PVT), Cognitive Load Theory (CLT) and Decision-Making Theory (DMT) are supporting theories for the design of the visualization and to support decision making process. This research also combining the cognitive and reasoning elements to strengthen the visualization results and

knowledge visualization preferences of the IHL domain decision maker are adequately attended to. This thesis demonstrates the development process of developing PKV conceptual model. The findings obtained equally showed that the proposed model is significantly satisfactory to be implemented to the real world which is in education sector. Based on the model, the research develops the prototype to strengthen the flow of the model and the prototype finally was tested through the usability testing. From the findings, there are the indications that the PKV model could be utilized to design and develop PKV prototype in supporting decision making process by providing solution and recommendations for decision maker in education environment specially to improve students' performance.

Understanding Internet usage behavior (IUB) is fundamental in developing future access networks and services that meet the students' need. It is hope that the findings of this research especially relate to IUB issues among students' during this pandemic, could contribute to the government national agenda which strives for quality education to empower people with the knowledge, skills and contribute to the societies. Emphasis on strengthening education is one of the needs-based approach economies that essential to be addressed by the government in line with the country's aspiration to achieve high value economic development by 2030.

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Appendix A Expert Review

Dear Dr,

EXPERT REVIEW OF PRESCRIPTIVE KNOWLEDGE VISUALIZATION (PKV) MODEL

I am Shakiroh Binti Khamis and currently pursuing my PhD in Information System at Universiti Utara Malaysia (UUM). I am delighted to inform you that you have been selected to participate in this research.

My PhD research proposes the **Prescriptive Knowledge Visualization (PKV) model** which aims to suggest a new model for Decision maker makes the best decision to identify the impact of internet usage for students academic performance especially in Higher Education Institutions.

One part of this research is to evaluate the proposed model. Through this review, I hope to evaluate the model in a few dimensions as listed in the review form.

You will see that the review questions give you ample opportunity to use your expertise, experiences, interests and creativity. It would be greatly appreciated if you could complete this evaluation form.

The information supplied will be treated as confidential and will be used for research purposes which may be reported anonymously in academic publications.

Please feel free to contact me by email (shakirohk@gmail.com) in regards to any queries or my supervisor Assoc Prof. Dr. Azizah Haji Ahmad (azie@uum.edu.my) and Assoc Prof. Dr. Mazida Ahmad (mazida@uum.edu.my).

Thank you for your time and assistance.

Best Regards,

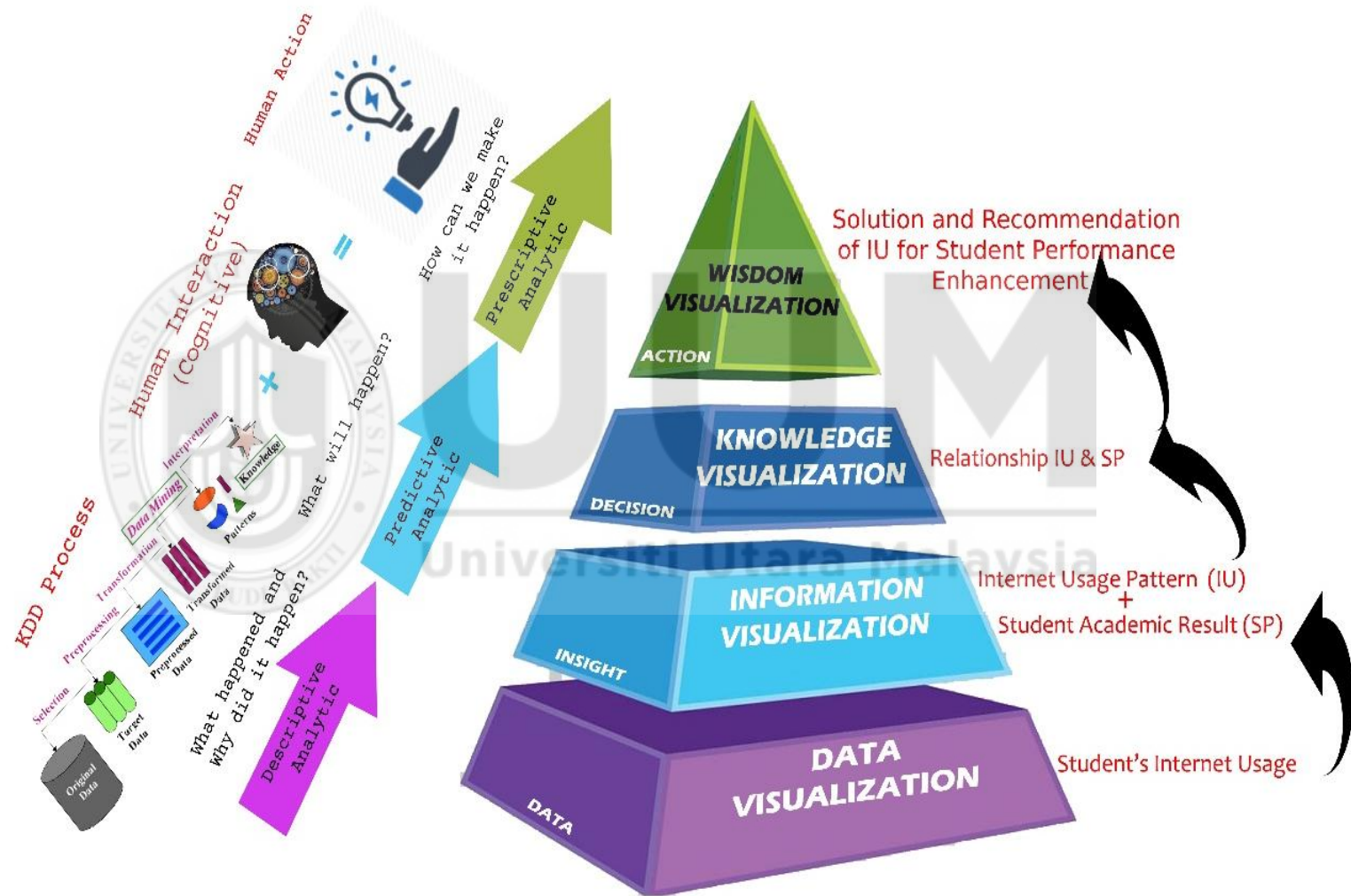
Assoc. Prof Dr. Azizah Haji Ahmad
Assoc. Prof Dr. Mazida Ahmad
Shakiroh Khamis

SECTION A: INSTRUCTION FOR EXPERTS

1. This booklet contains 14 pages.
2. SECTION B contains the model and explanations
3. SECTION C contains the questionnaires s validation form for PKV Model that needs to be completed.
4. SECTION D is validation form for PKV Questionnaires that need to be completed.



SECTION B: THE PRESCRIPTIVE KNOWLEDGE VISUALIZATION (PKV) CONCEPTUAL MODEL



THE PKV EXPLANATIONS

Brief explanations related to the selected features in the PKV conceptual model for elderly are reviewed in the table below. It is to portray the experts the background of the model features and their appropriateness due to the previous studies.

ITEM	EXPLANATION
Data Analytics	<i>Analytics</i> uses mathematics, statistics, predictive modeling and machine learning to find patterns in data. Big data analytics examines large amounts of data to uncover hidden patterns, correlations and other insights. With today's technology, it's possible to analyze large data and get answers from it almost immediately. Big data analytics helps organizations harness their data and use it to identify new opportunities. According to Gartner (2012), there have different types of analytics which will help for decision making process. a) Descriptive Analytics / Diagnostic Analytics Descriptive analytics is the simplest form of analytics and it is the first step in a complex process, which

provides a solid foundation for further analytics. The objective of descriptive analytics is answering the question of what happened rather than why this happened. It is limited to answer only what happened. The interesting about descriptive analytics is the fact that powerful insights can be gained with some simple arithmetic operations such as mean, median, mode, or minimum and maximum values.

Descriptive analytics juggles raw data from multiple data sources to give valuable insights into the past. However, these findings simply signal that something is wrong or right, without explaining why. For this reason, highly data-driven companies do not content themselves with descriptive analytics only and prefer combining it with other types of data analytics.

In this study, researcher will use descriptive analytics to determine the relationship between two variables: Students' internet usage and student performance. Descriptive analysis was then performed to look at the frequency of internet usage, the amount of time spent on the internet, the most frequent internet access points, Internet browsing goals and most used internet services. This data is analyzed using SPSS version 24.

Diagnostic analytics goes beyond basic reporting of past performance and looks for patterns and interdependencies in the data that can explain why something went right or wrong. It is usually combined with descriptive analytics and draws from the same data source. However, it provides the context that makes conclusions about cause and effect more reliable. In other words, it gives meaning to the results of a

descriptive analysis.

In this study, researcher will use diagnostic analytics to diagnose information on Internet usage patterns and on Internet attitudes and behaviours consisted of 11 categories which is underlying web 2.0. In particular, the Diagnostic analysis for Internet usage pattern based on 11 categories was used as a tool to categorize the type of Internet behaviour.

b) Predictive Analytics

Predictive analytics tells what is likely to happen. It uses the findings of descriptive and diagnostic analytics to detect tendencies, clusters and exceptions, and to predict future trends, which makes it a valuable tool for forecasting. Despite numerous advantages that predictive analytics brings, it is essential to understand that forecasting is just an estimate, the accuracy of which highly depends on data quality and stability of the situation, so it requires careful treatment and continuous optimization.

When descriptive analysis has successfully describing students' online behaviour, then predictive analytic will come across by using these data to predict student performance. The results are generated in the form of algorithms and patterns and will formulate the model. To visualize, categorize, and summarize data, descriptive statistics including frequency distribution tables are easy to use and to investigate hypotheses and

	test the theoretical model of the study, Spearman's correlation reference statistics are used. c) Prescriptive Analytics The purpose of prescriptive analytics is to literally prescribe what action to take to eliminate a future problem or take full advantage of a promising trend. This state-of-the-art type of data analytics requires not only historical data but also external information due to the nature of statistical algorithms. Besides, prescriptive analytics uses advanced tools and technologies, like machine learning, business rules and algorithms, which makes it sophisticated to implement and manage. The beauty about prescriptive analytics is, it enables to suggest recommendations and suggestion based on the predictive results. In this study, prescriptive analytic will embed human skills to give recommendation based on the results which is visualize by dashboard. Prescriptive analytic will recommend by answering “how should you do” which is next action after the question “What is most likely to happen based on my current result, and what can I do to change that outcome?”
Visualization Structure	Visualization is the strongest potential growth among options for big data analytics (Russom, 2011). According Miller and Mock (2013), Visualization involves presenting analytic results to decision makers as a static report or an interactive application that supports the exploration and refinement of results. The goal is to provide key stakeholders

with meaningful information in a format that they can readily consume to make critical decisions. Visualizing data and results of analyses provide a way of easily communicating data at all levels of a business, and can reveal surprising patterns and relationships. In visualization, we use the terms data, information and knowledge extensively (Chen et al., 2009). In many cases, they indicate different levels of abstraction, understanding or truthfulness. The data-information-knowledge-wisdom(DIKW) hierarchy is a popular model for classifying human understanding. The origin of this hierarchy by Russell Ackoff's (1999) definition of data, information, knowledge and wisdom as follows:-

a) Data Visualization (DV)

According to Ackoff (1999), data is a symbol that represent the properties of objects and events but when using visualization techniques, data visualization is the communication of data in a visual manner, or turning raw data into insights that can be easily interpreted by your readers. Data visualization relates to the methods used in graphics to transmit data or information by encoding it as visual objects (e.g. points, rows or bars). The objective is to obviously and effectively transmit data to customers. In data analysis or data science, it is one of the steps.

b) Information Visualization (InfoVis)

Card et al. (1999) define information visualization as the use of computer-supported, interactive, visual representations of abstract data to amplify cognition. This definition is well established and represents a broad consensus among computer scientists active in this field. InfoVis helps for information exploration and visual information seeking.

c) Knowledge Visualization (KV)

Eppler (2004) define Knowledge visualization is using the visualization to transfer the information become knowledge but the aims is to improve the transfer and creation of knowledge among people by giving them richer means of expressing what they know. InfoVis and KV are both exploiting human innate abilities to effectively process visual representations, but the way of using these abilities is different. While infoVis typically helps to improve information retrieval, access and presentation of large data sets, KV primarily aims at augmenting knowledge-intensive communication between individuals.

	d) Wisdom Visualization (WV) Addressing the concept of Wisdom visualization along with data, information and knowledge visualization is an attempt to push the boundaries toward a deeper understanding of the quality of data we visualize. In many literature, wisdom has been avoided due to the impossibility to achieve consensus and understanding of its meaning (Scagnetti, 2009). Based on rowley (2007), they do not see information and knowledge contributing to wisdom. But from Figueroa(2009), wisdom is all about the future, it relies on knowledge and pattern models, giving an exponential competitive advantage. Wisdom come from pure human skills and the combination of AI. The concepts of insight and intelligence is the metaphore for wisdom.
Method / Techniques	a) Knowledge Data Discovery Process (KDD) The term Knowledge Discovery (KDD) in Databases refers to the broad process of finding knowledge in data, and emphasizes the "high-level" application of particular data mining methods. It is of interest to researchers in machine learning, pattern recognition, databases, statistics, artificial intelligence, knowledge acquisition for expert systems, and data visualization. The unifying goal of the KDD process is to extract knowledge from data in the context of large databases. The overall process of finding and interpreting patterns from data involves the repeated application of the following steps:

- Data cleaning and preprocessing.

In this process will includes basic operations, such as removing noise or outliers if appropriate, collecting the necessary information to model or account for noise, deciding on strategies for handling missing data fields, and accounting for time sequence information and known changes, as well as deciding DBMS issues, such as data types, schema, and mapping of missing of unknown values.

- Data reduction and projection.

Then followed with data reduction and projection which includes finding useful features to represent the data, depending on the goal of the task, and using dimensionality reduction or transformation methods to reduce the effective number of variables under consideration or to find invariant representations for the data.

- Data Mining Approach

Although data mining has been successfully applied in the business world for some time now, its is still comparatively new in higher education. Its use is intended for identification and extraction of new and potentially valuable knowledge from the data. Using data mining the aim was to develop a model which can

derive the conclusion on students' academic success. Data mining represents promising areas of researches in education, and it has specific requirements which other fields lack. A very comprehensive review of data mining in education from 1995 to 2005 is published in 2007 by Romero and Ventura. One of the educational problems that are solved with data mining is the prediction of students' academic performances, whose goal is to predict an unknown variable (outcome, grades or scores) that describes students. The estimation of students' performances includes monitoring and guiding students through the teaching process and assessment.

Romero et al. (2008) compared different methods of data mining in order to predict final assessment based on the data obtained from the system of e- learning. Zekic-Susac, Frajman-Jaksic and Drvenkar (2009) created a model for predicting students' performance using neural networks and classification trees decision-making, and with the analysis of factors which influence students' success. Kumar and Vijayalakshmi (2011) using the decision tree predicted the result of the final exam to help professors identify students who needed help, in order to improve their performance and pass the exam.

In this study, Waikato Environment for Knowledge Analysis (WEKA) was used to build software tool for all experiments. WEKA is an open source machine learning package developed in Java; it is a collection of machine learning algorithms for data mining tasks. It contains tools for data preprocessing, classification,

regression, clustering, association rules, and visualization. There are many machine learning algorithms implemented in WEKA including Bayesian classifiers, Decision Trees, Rules, Functions, Lazy classifiers and miscellaneous classifiers. It is also well-suited for developing new machine learning schemes. It has a GUI Chooser from which any one of the four major WEKA applications can be selected. For the purpose of this study the Explorer application was used. This study deals with classifier algorithms, functions (multilayer perceptron) and uses the default options presented by Weka for each algorithm. All the machine learning techniques that are used in this study are implemented in WEKA so that they will be easily and fairly compared to each other. The latest Windows version of Weka 3.7.7 has been used.

- Interactive Dashboards

An interactive dashboard is a data management tool that tracks, analyzes, monitors, and visually displays key business metrics while allowing users to interact with data, enabling them to make well-informed, data-driven, and healthy business decisions. Dashboard is a new techniques and approaches that help to transform insights into actions. This techniques to embed insights will gain in value by generating results that can be readily understood (Steve et al., 2011). In this study, we will build an interactive website with a dashboard that displays updates on students' internet activity and students academic results. The data will visualize using

python and the dashboard will show the relationship results between these two variables. The researcher will use a basic knowledge of Python, Flask, and JavaScript (ES6 syntax) to develop the system.

- Interpreting mined patterns/ Consolidating discovered knowledge.

Interpretation: includes interpreting the discovered patterns and possibly returning to any of the previous steps, as well as possible visualization of the extracted patterns, removing redundant or irrelevant patterns, and translating the useful ones into terms understandable by users. includes incorporating this knowledge into the performance system, taking actions based on the knowledge, or simply documenting it and reporting it to interested parties, as well as checking for and resolving potential conflicts with previously believed (or extracted) knowledge. In this process, student's internet usage pattern been discovered and will be visualize using WEKA and from there the system will predict what will happen to the students CGPA based on their pattern.

b) Cognitive (Human Interaction)

Cognitive effort has been defined as the total amount of cognitive resources needed to complete a task and it includes cognitive resources of perception, memory and judgment (Cooper-Martin, 1994; Russo & Doshier, 1983). The function of cognitive efforts work as cognitive tools which is involve human participations from

various different level of thinking to leverage in decision making process. It will involve visualization in the first place as the bottom up to process the data and transform the data to the meaningful information. The role of visualization is to leverage the functioning of the human visual system in an effort to provide insight about abstract information (Hearst, 2009).

Previous studies have shown that many of the existing research have concentrated on the visualization and the role of cognitive process. Patterson (2014) present a human cognition framework for information visualization. This framework emphasizes on how top-down cognitive processing enables the induction of insight, reasoning, and understanding, which adopted by Patterson (2012). another research done by Mnguni (2014) to explore the cognitive process of visualization to present a model that could be used to study visual literacy empirically within science education. The researcher study and explore various theories related with cognitive process in visualization from different domain. They are discussing the critical aspects in term of how can visual models construct the knowledge and the theoretical part in cognitive process of visualization. The construction knowledge from visualization adopted from Mayer (2002) based on cognitive theory of multimedia learning which is related to a constructivist epistemology of learning. According to Mayer (2003) there consists of three stages during learning the visualization process which are, comprehension of visual information, processing of this information in cognitive structures, and externalization of information as visual

	models. From the visualization itself, it can produce the ability to select and effectively use a set of cognitive skills for perceiving, processing and produce visual models. c) Solution and Recommendation Prescriptive analytics is the most sophisticated type of business analytics and can bring the biggest intelligence and value to businesses and aims at suggesting and brescribing the best decision options in order to take advantage of the predicted future utilizing large amounts of data (Šikšnys & Pedersen, 2016). Prescriptive analysis has two levels of human intervention: decision support by giving advice and automation of decisions, e.g. implementation of the prescribed action (Gartner, 2017). Optimization methods have gathered the research interest in the context of prescriptive analytics in order to derive optimal solutions based on several objectives. Prescriptive analytics provide intelligent recommendations for the optimal next steps for almost any application or business process to drive desired outcomes or accelerate results (Fallon, 2015).
Domain	a) Students's Internet Usage The use of the internet is useful to the world especially to students. Students' occupy the largest share of the

benefit from it because they are more interested in new technologies, applications and developments so they are affected more than other age stages (Siddiqi & Memon, 2016). Study conducted by Kirci (2015) in Turkey have found the use of the Internet focused on education and the computer usage preferred after reaching easy Internet access around 2000s. Another study Nachmias, Mioduser and Shemla (1999) to examines the extent and characteristics of Internet usage among 384 junior-high and high school students in Israel shows that the Internet is being used by about half of the research population, with the main use being for communication. Search for information comes only in the second place and low degree of connection was found between Internet usage and school practice. Meanwhile, a study conducted by Omekwu, Eke and Odoh (2014) on undergraduate students University of Nigeria, Nsukka found that most positively using social networking sites. The findings of this study show that UNN undergraduate students use social networking sites for different purposes

b) Internet Usage Pattern

The Internet is widely used for various purposes, such as communicating information, conducting business, and personal entertainment. Information regarding Internet usage may thus be valuable, as it indicates the

frequency and duration that a particular website is used or a user's preference among various websites. In some cases, such as in a marketing study, Internet usage analysis may be performed to understand customers' online preferences. For example, the on-line user's activities may be monitored and used as a basis for targeting advertisements to the user. In some other cases, the human resource department of a corporation may utilize Internet usage analysis to monitor employees' Internet activities.

For the last two decades, internet usage among the students has been the most targeted research area in academic performance analysis (Ani, O.E., 2010). Moreover, various studies have been focusing on the behavior to find out the patterns related to internet usage and their impact on their respective performances. several techniques used to analyze user activities on the Internet, In this study, internet usage pattern. proxy log analysis has been used to determine how often students “surfs” the Internet per day. Proxy logs may be created by various tools on a proxy server, such as a Microsoft Proxy Server 2.0 or a Microsoft ISA Server. Proxy logs record information about Internet events (known as “hits”), such as the URL of a hit, and the time the URL is downloaded. Based on such proxy logs, Internet usage time and usage frequency could be determined.

c) Student's Academic Result

Graded Point Average (GPA) is a commonly used indicator of academic performance. Many Universities set a minimum GPA that should be maintained in order to continue in the degree program. In some University, the minimum GPA requirement set for the students is 1.5. Nonetheless, for any graduate program, a GPA of 3.0 and above is considered an indicator of good academic performance. Therefore, GPA still remains the most common factor used by the academic planners to evaluate progression in an academic environment (Sansgiry, S. S. & Bhosle, M., 2006). Many factors could act as barriers to students attaining and maintaining a high GPA that reflects their overall academic performance during their tenure in University. These factors could be targeted by the faculty members in developing strategies to improve student learning and improve their academic performance by way of monitoring the progression of their performance (Oyelade, O.J, Oladipupo, O.O, & Obagbuwa, I.C, 2010). Therefore, performance evaluation is one of the bases to monitor the progression of student performance in higher Institution of learning. In the study, students GPA was determine as a results to see the impact of students academic performance.

d) Relationship Internet Usage and Student's Performance

The literature on the impact of Internet usage and student's academic performance on students has shown mixed results. The arguments on the relationship between Internet usage and students' performance have been

	classified into two groups: the first group supports the positive relationship between them (Siraj et al., 2015; Chang et al., 2014; Kumar & Manjunath, 2012; Ogedebe, 2012; Oskouei, 2010), whereas the second group claims that Internet usage does not support on the students' performance even give negative impact on the students (Cerretani, Iturioz & Garay, 2016; Wanajak, 2011; Englander, Terregrossa & Wang, 2010). However there also a study that provides no significant relationship between the two variables (Ellore, Nirajan & Brown, 2014). It shows that past studies related to Internet usage on the academic performance give inconsistent results (Englander, Terregrossa & Wang, 2010) and few have shown contradicting results otherwise.

SECTION C : QUESTIONNAIRE

SECTION A : Background of Respondents

- 1) Age : _____ years old
 2) Highest Education Level : _____
 3) Gender : Male Female
 4) Experiences : _____

SECTION B : Evaluations Form

/														Strong Disagree Strong Agree Least Important More Important							
Dimensions	1	2	3	4	5	6	7	8	9	10	Remarks	1	2	3	4	5	6	7			
1- Complexity																					
a) The proposed model is clear and understandable.																					
b) Using the proposed model does not require a lot of mental effort.																					

c) The proposed model is not cumbersome to use.																				
d) Using the proposed model does not take too much time from my normal duties.																				
e) The proposed model is simple and can be implemented easily.																				
2. Visibility																				
a) The proposed model makes clear and visible to decision maker to make decision.																				
b) The proposed model allows me to determine the completeness of the process before decision making.																				
c) The phases in the proposed model are easily followed.																				
d) The proposed model allows me to intelligently digest and make relevance decision making.																				
3. Flexibility																				
a) The proposed model is adaptive and responsive to changing in user needs.																				

b) The proposed model is flexible with minimal planning.																				
c) All the concepts and components included are strictly necessary.																				
4. Clarity																				
a) The phases in the proposed model are easily followed.																				
b) The proposed model as a whole is workable.																				
c) Steps or activities included are easy to apply.																				
5. Manageability																				
a) The proposed model to be capable of being managed or controlled.																				
b) The proposed model allows self-monitoring to be followed.																				
c) The proposed model is consistent and easy to manage.																				
d) The proposed model is organized and well-structured.																				

6. Practicality																				
a) The proposed model is practical to be implemented in the real world.																				
b) The proposed model produces results that can be used for future improvement.																				
7. Effectiveness																				
a) Using the proposed model increases my job performance and productivity.																				
b) Using the proposed model enhances the quality of my work.																				
c) Using the proposed model makes it easier to do my job.																				
d) The advantages of using the proposed model outweigh the disadvantages.																				
e) Using the proposed model produces the better result for which is intended for decision making.																				

Institution:

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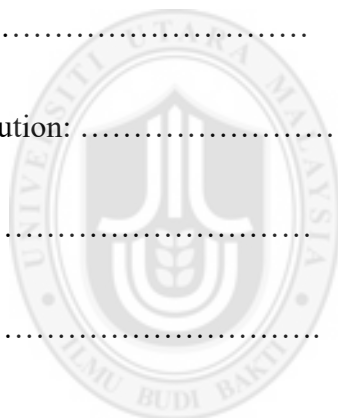
Phone:

Email:

Address of the Institution:

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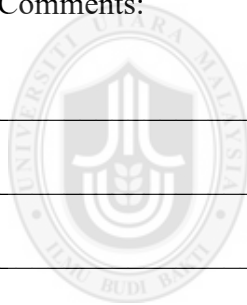
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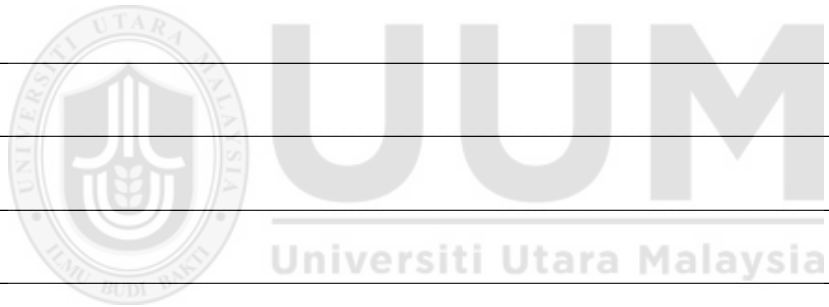
SECTION E: VALIDATION BY EXPERT (The PKV Model)

I, hereby certify and validate that the “**Prescriptive Knowledge Visualization (PKV) Model**” produced by the researchers from College of Arts and Sciences , Universiti Utara Malaysia is suitable to be used as the conceptual model for Internet Usage and Student Performance for decision making. It has been checked and the general comments are as follows:

General Comments:



UUM
Universiti Utara Malaysia



Thank You.

VALIDATION BY EXPERT

Signature : _____

Name : _____

Experience in teaching: _____

Qualification: _____

Name and address of Institution/University:



Institution stamp:

Date: _____

Appendix B Instrument for Heuristics Evaluation

Introduction

The purpose of this instrument is to evaluate the Prescriptive Knowledge Visualization System (PKVS) using the heuristics evaluation.

The information supplied will be treated as confidential and will be used for research purposes which may be reported anonymously in academic publications.

Please feel free to contact me by email (shakirohk@gmail.com) in regards to any queries or my supervisor Assoc Prof. Dr. Azizah Haji Ahmad (azie@uum.edu.my) and Assoc Prof. Dr. Mazida Ahmad (mazida@uum.edu.my).

Thank you for your time and assistance.



Interpretation of the scale

1= Strongly Disagree, 2 = Disagree, 3 = Neutral, 4= Agree, 5 = Strongly Agree

DIMENSIONS	Scale					Sources
	1	2	3	4	5	
VISIBILITY						
This system can display the information (Virtual Results) in a well-structured manner.						I
All instructions are visible and self-explanatory						I
Navigation options in this application such as (Links, shortcuts, home, back, forward, etc) are displayed in visible manner.						I
The data in this system concisely presented.						I
This system has all the functions and capabilities I expect it to have.						I
I like the interface of this system						J
The interface for this system is pleasant.						I
The organization of information in the system screen was clear.						I
FLEXIBILITY	1	2	3	4	5	
I felt fully in control when using this system.						S

This system has customizable feature.						I
In this system the design for data entry is flexible.						I
The data can be used, manipulated and/or processes in easy manner.						S
LEARNABILITY	1	2	3	4	5	
In this system the data grouping reasonable for easy learning.						I
In this system promotes learnability to make it accessible for infrequent usage.						S
In this system, the grouping of menu options is logical.						S
I believe I could become productive quickly using this system.						I
THE APPLICATION BEHAVIOR	1	2	3	4	5	
This application enhances user efficiency through a consistency rapid response rate.						A
The application behavior is consistent.						A
The information was effective in helping me complete the tasks.						A
It was easy to find information I needed.						I
Whenever I made a mistake using the system, I could recover						J

easily and quickly.						
I was able to complete the tasks quickly using this system.						A
REAL-TIME DECISION MAKING	1	2	3	4	5	
This system provides the information visualization functionality (comparison charts, graphs to reveal trends etc) to assist in decision making.						A
In this system, the breadth and depth of the data provide sufficient coverage for all data resources.						A
In this system, data is received on time to take suitable actions and decisions.						A
In this system, the data is always live data and up to date.						A
In this system, the data was cleaned, cleansing and profiling, so there are almost no errors in the data.						A

A = Jooste et al., 2013

S = Lin, Choong & Salvendy, 1997

I = Lewis, 1995

Institution:

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Phone:

Email:

Address of the Institution:

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In this manual, you will find detailed instructions and explanations to help you understand the system's features and functionalities. We have organized the content in a user-friendly manner, allowing you to quickly locate the information you need.

Before diving into the details, it is essential to understand the purpose and benefits of our system. Our system is designed to simplify complex tasks, automate processes, and enhance efficiency in decision making. It leverages advanced technologies to streamline operations, improve productivity, and provide an intuitive user experience.

Throughout this manual, we will introduce you to the key components of the system, explain how they interact with each other, and guide you through their usage. Additionally, we will highlight best practices and offer insights to help you make the most of our system's capabilities.

We value your feedback and suggestions for improving our system and its documentation. If you have any questions, concerns, or recommendations, please feel free to reach out to our shakirohk@gmail.com. We are committed to assisting you in successfully implementing and utilizing our system.



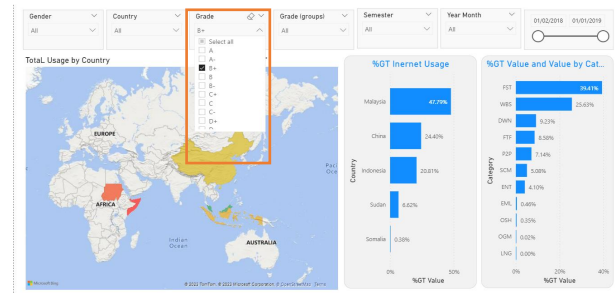
PKVS

System Manual

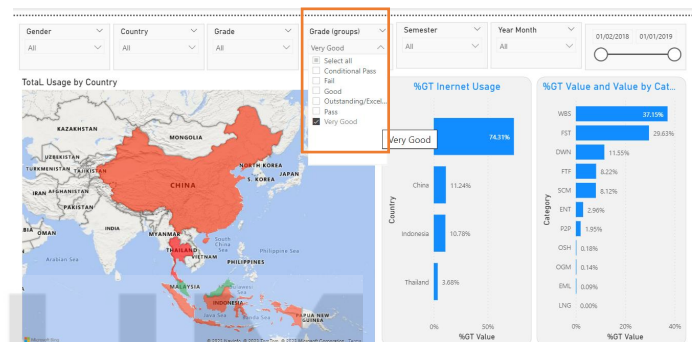
SYSTEM OVERVIEW

The Filter Bar on Top of the PKVS Screen

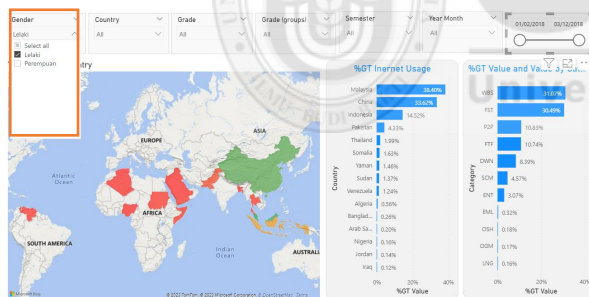
The Filter Bar consists of Gender, Country, Grade, Grade(groups), Semester, Year/Month and Date. User can select the Filter Bar by select the drop-down list and choose any option with the mouse. The system will automatically visualize data in the GEO MAP and display the percentage of Internet Usage by COUNTRY and percentage of the Internet Usage by CATEGORY.



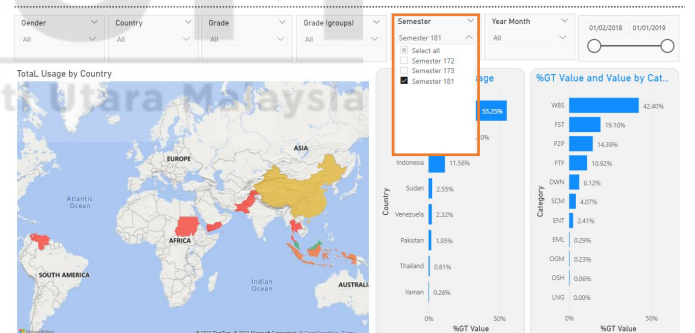
❖ Filter by Grade (groups)



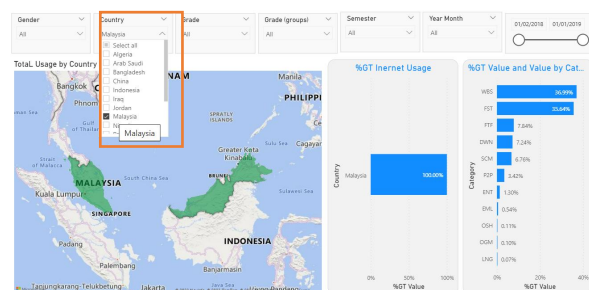
❖ Filter by Gender



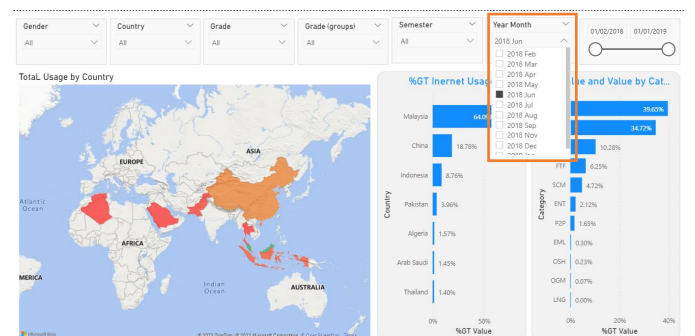
❖ Filter by Semester



❖ Filter by Country



❖ Filter by Year/Month



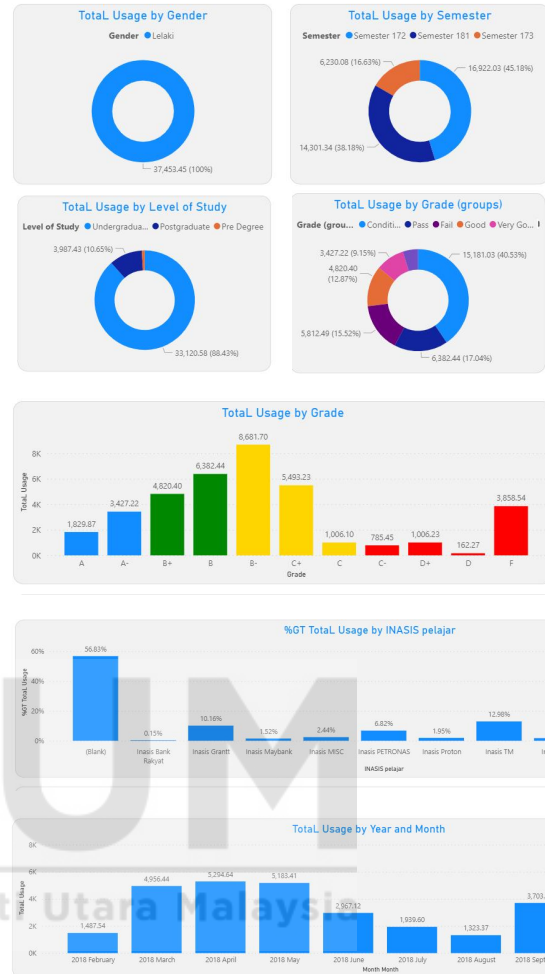
❖ Filter by Grade

❖ Filter by Date

❖ Descriptive Analysis

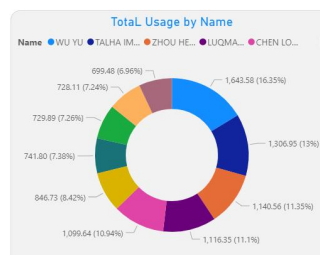
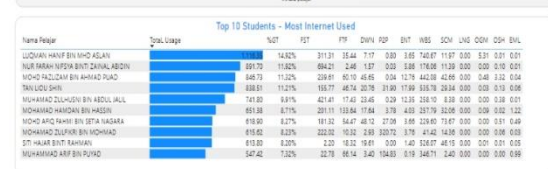
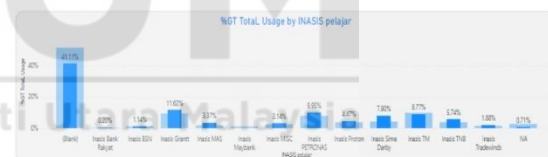
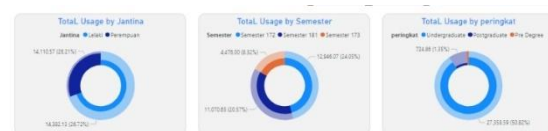
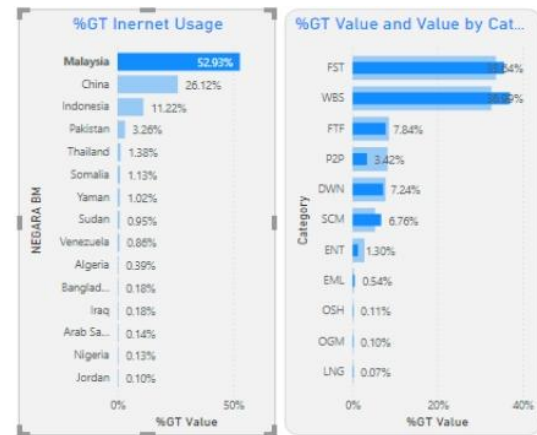
User can view the student demographic based on the user preferences. There are a number of categories that user can view by using pie chart and graph.

- Gender
- Semester
- Level of Study
- Grade (Groups)
- Grade
- Inasis (College)
- Month/Year



❖ Predictive Analysis

User can view the predictive results in the form of graph. When the system clicked at certain figure, it will automatically visualize the result through the process of predictive analytic.



❖ Prescriptive Analysis

User can view the prescriptive analysis page of PKV prototype. The system will list down the recommendation based on predictive analytic result. The system will produce the knowledge base on the solutions of internet usage activities and propose 3 highest weighted recommendations to the user (decision maker). Users can easily choose the option given by the system for a targeted interventions and support programs.



Allow user to do peer-to-peer (3% will increase the student performance)

Do not allow student to download, slow down bandwidth to 30Mbps

cultivate student to do more online shopping because through the research online shopping will make student happy and increase student performance 3%.



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